The Risk and Expected Return of Stocks and Corporate Bonds*

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February 2026

Abstract

We study the joint dynamics of stocks and corporate bonds using a structural credit risk model in which firms' unlevered asset returns and volatilities are driven by systematic risk factors. The model captures fluctuations in stock and bond volatilities, leverage, and credit spreads at the market, industry, and firm levels. Its expected return forecasts exceed Martin (2017)'s lower bound for equities and display pronounced countercyclical spikes for corporate bonds. These forecasts significantly predict realized returns at both the market and firm levels, outperforming benchmarks. We find that systematic variance risk commands a substantially larger premium in corporate bonds than in equities.

Keywords: Conditional risk premia, structural credit models, return predictability, equity-credit market asset pricing.

JEL Classification Codes: G10; G12; G13.

*We thank Mikhail Chernov, Jaewon Choi, Guanglian Hu (discussant), Jiantao Huang (discussant), Kris Jacobs, Alexandre Jeanneret, Philippe Mueller, Andrew Patton, Nikolai Roussanov, and Paul Whelan, as well as seminar and conference participants at McGill University, the 2025 Melbourne Asset Pricing Meeting, the 2025 SFS Cavalcade Asia-Pacific, the TIP Group, and Victoria University, for helpful comments. We gratefully acknowledge financial support from the Canadian Derivatives Institute.

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Modern asset pricing seeks to understand how economic risks are shared across financial markets and how this sharing shapes expected returns. Yet despite decades of progress, much of the empirical literature continues to treat major asset classes in isolation. Stocks and corporate bonds—the two most important claims on firms' cash flows—are typically analyzed separately, despite their exposure to common underlying shocks. This separation obscures a fundamental question in asset pricing: how aggregate risks transmit across the capital structure and map into expected returns for securities with distinct payoff profiles. In this paper, we study the joint dynamics of stocks and corporate bonds within a structural framework to provide a coherent view of their risks and expected returns.

Studying equity and credit markets jointly requires a unified framework in which corporate securities derive their value from common underlying sources of risk. While abstracting from firms' default risk may appear relatively innocuous in stock-only analyses, existing evidence shows that default risk helps explain several prominent stock pricing anomalies.[1] Once stocks and corporate bonds are considered jointly, explicitly accounting for default risk becomes essential for understanding how aggregate shocks transmit along the capital structure.

In this context, structural credit risk models provide a natural foundation by endogenizing the values, risk exposures, and expected returns of all corporate claims through the dynamics of firms' unlevered asset values. Although the literature following Merton (1974) is extensive, it has largely focused on matching point-in-time pricing moments or on studying one market while taking the pricing of the other as given. As a result, relatively little is known about whether these models can jointly characterize stock and corporate bond returns within standard asset-pricing tests, particularly those used in the analysis of factor models.

Our contribution is to rigorously estimate a particular structural model, grounded in recent theoretical advances, and to show that it provides a disciplined empirical characterization of the dynamics of risk and expected returns of stocks and corporate bonds. The model fits a broad set of moments, including stock and bond volatilities, leverage, and credit spreads. It delivers expected return forecasts of plausible magnitudes with strong predictive power across market, industry, and firm-level tests. In the cross section, it explains a substantial share of return variation across stock and bond portfolios sorted on standard firm characteristics. Exploiting the structural nature of the framework, we further document that aggregate asset variance risk

[1]For example, Vassalou and Xing (2004) show that stock return anomalies depend on firms' exposure to distress risk, while Doshi et al. (2019) highlight that leverage can materially affect conclusions drawn from asset-pricing tests.

commands a significantly larger premium in corporate bonds than in stocks, highlighting how aggregate risks are transmitted asymmetrically across the capital structure.

Our model builds on recent advances in structural credit risk modeling, drawing in particular on the frameworks developed by Du, Elkamhi, and Ericsson (2019), Collin-Dufresne, Junge, and Trolle (2024), Dickerson, Fournier, Jeanneret, and Mueller (2023), and Doshi, Ericsson, Fournier, and Byung Seo (2024).[2] Relative to this literature, our novelty lies in using this class of models as an empirical asset-pricing laboratory to jointly study stock and corporate bond returns in the context of standard asset-pricing tests.

Our theoretical analysis derives the return and volatility dynamics of stocks and corporate bonds, as well as those of their corresponding market and industry portfolios. In the model, unlevered firm asset values are driven by a single aggregate asset risk factor with stochastic and priced variance. Although assets are exposed to only one fundamental shock, the non-linear mapping from unlevered asset values to corporate claim prices implies that two sources of systematic risk arise endogenously in stock and bond returns: aggregate asset risk and aggregate variance risk, the latter capturing innovations to the variance of the aggregate asset factor. Consistent with leading asset-pricing frameworks, the premia associated with aggregate asset and variance risks are linear in aggregate asset variance, that is, in aggregate unlevered uncertainty.

While numerous priced factors have been identified when stocks or corporate bonds are studied in isolation, economically motivated sources of risk that are common to both markets remain elusive.[3] Although the framework could be extended to incorporate additional systematic risks, we therefore focus on the pricing implications of aggregate asset and variance risks, two fundamental sources of systematic risk well anchored in theory.[4]

Crucially, the model illustrates how differences in cash-flow contingencies between stocks and corporate bonds generate distinct and highly state-dependent exposures to these risks. Unlike

[2] See also McQuade (2018).

[3] For example, Fama and French (1993) show that term and default spread factors explain bond returns, while equity returns are primarily driven by market, size, and value factors. Choi and Kim (2018) find that investment and momentum factors are priced inconsistently across stocks and bonds. More recently, Dickerson et al. (2023) show that firm- and aggregate-level liquidity measures explain only a limited portion of stock–bond comovement.

[4] The central role of market risk is emphasized by Merton (1973) in the context of dynamic asset allocation, and its empirical relevance is well documented in Fama and French (1993) and Dickerson, Mueller, and Robotti (2023), among many others. The importance of variance risk for equities and their derivatives is studied in Bansal and Yaron (2004), Ang, Hodrick, Xing, and Zhang (2006), Bollerslev, Tauchen, and Zhou (2009), Todorov (2010), and Eraker and Wu (2017).

traditional regression-based factor approaches, risk exposures in the model evolve endogenously with economic conditions, reflecting variation in aggregate asset variance and firm default risk. As a result, expected returns of stocks and corporate bonds are jointly driven by time variation in both factor risk premia and state-dependent exposures.

The empirical analysis is conducted on a sample of over 764 firms included in the S&P 500 index between 1997 and 2022 with actively traded corporate bonds. Corporate bond returns are duration hedged to isolate credit risk by removing variation driven by interest rate fluctuations, which also aligns the data with the model's assumption of a constant risk-free rate.[5] The structural parameters of the model are estimated by maximum likelihood, and the latent state variables—unlevered firm value and aggregate asset variance—are filtered jointly within the estimation procedure.

The empirical validation proceeds at multiple levels of aggregation, beginning with market-level dynamics. The market-level estimation targets key dimensions of equity and credit risk, including the joint behavior of equity and corporate bond market volatilities, as well as stock and bond volatilities, credit spreads, and leverage of a market-wide representative firm.[6] Overall, the model provides a strong fit, closely tracking both the levels and time-series dynamics of these variables.

Model-implied market expected returns are economically plausible in magnitude and exhibit meaningful time variation. The equity risk premium exceeds the SVIX benchmark of Martin (2017) throughout the sample, while the corporate bond risk premium displays pronounced countercyclical spikes during periods of financial stress. Model risk premia possess significant and economically meaningful in-sample predictive power for next-month market returns. For both markets, predictive regressions yield slope coefficients statistically indistinguishable from one and small, statistically insignificant average pricing errors.

A formal out-of-sample evaluation confirms that the model's predictive performance extends beyond the estimation sample. Over a 20-year evaluation period, the model forecasts deliver economically significant out-of-sample R^2, 2.88% for the stock market and 7.53% for the credit market, and compares favorably to a broad set of leading return predictors.

We next examine whether the model's performance extends to the 12 Fama–French indus-

[5] Duration hedging eliminates risk compensation and return predictability arising from fluctuations in the term structure; see van Binsbergen, Nozawa, and Schwert (2025).

[6] All corporate bond return and volatility measures are computed using duration-hedged returns; for brevity, the term "duration-hedged" is omitted throughout the remainder of the introduction.

tries. Conditioning on market-level estimates of systematic risks, each industry's representative firm is characterized by only three free parameters and a single state variable—the unlevered asset value. Despite substantial cross-sectional heterogeneity across industries, the model performs well, capturing both the levels and much of the time-series variation in industry-level stock and bond volatilities, leverage, and credit spreads. Turning to predictability, the model generates statistically significant expected return forecasts for the majority of industry portfolios—eight out of twelve for stocks and eleven out of twelve for corporate bonds.

Although aggregate asset and variance risks—and their associated risk premia—are common across securities, their contributions to return dynamics differ markedly between stocks and corporate bonds due to heterogeneity in exposures. Consistent with equities' greater upside potential, the model predicts that stock betas to aggregate asset risk are substantially larger than those of bonds, implying an annual asset risk premium of about 9% for the equity market—more than four times that of the credit market. By contrast, the variance risk premium in stocks is negative and economically small on average. In corporate bonds, however, variance risk commands a substantial premium, accounting for nearly half of total expected returns. We further show that most of the model's predictive power for stock market returns is attributable to the aggregate asset risk premium, whereas for the credit market roughly half of the variation in future returns is driven by the aggregate variance risk premium. Decomposing expected returns at the industry level corroborates these findings.

Why does variance risk matter asymmetrically across the capital structure? In a framework without debt tax shields or bankruptcy costs, as in Merton (1974), equity and debt have equal but opposite dollar sensitivities to aggregate variance risk.[7] The introduction of these features breaks this symmetry. The tax shield adds to firm and thus equity value. While increased asset volatility benefits the embedded call option in equity, the potential loss of the tax shield offsets this, and reduces its exposure to variance risk. In contrast, bankruptcy costs amplify debtholders' downside when volatility increases and default becomes more likely. Consequently, corporate bonds exhibit a stronger exposure to aggregate variance risk than stocks—a key asymmetry that arises once tax shields and bankruptcy costs are introduced.

Our final empirical exercise relates to the credit literature that emphasizes heterogeneity across individual firms by relaxing the representative-firm assumption. Prominent examples

[7]In Merton (1974), asset variance is constant and enters the model as a parameter. The equal but opposite sensitivities of equity and debt therefore refer to dollar sensitivities with respect to the asset variance (or volatility) parameter, rather than to a priced source of stochastic variance risk.

include Bhamra, Kuehn, and Strebulaev (2010b), and Feldhütter and Schaefer (2018). Building on this line of work, we estimate firm-level asset value dynamics for the full cross-section of firms in our sample and generate model-implied expected return forecasts for each firm's stock and corporate bond. Firm-level predictive panel regressions yield slope coefficients statistically indistinguishable from one and small, statistically insignificant average pricing errors for both markets. Relative to alternative benchmark frameworks—including intermediary capital, liquidity, Fama–French five-factor, and IPCA models—the structural model delivers stronger firm-level predictive performance and substantially higher explanatory power for next-month returns.

In the cross section, unconditional regression-based betas for both stocks and corporate bonds align closely with the model-implied average factor exposures. This result holds across portfolios sorted on alternative measures of default risk and when regression factor loadings are estimated using mimicking portfolios for aggregate asset and variance risks. Beyond factor exposures, the model explains a substantial share of return dispersion across portfolios sorted on firm characteristics such as size, book-to-market, and leverage. For equities, cross-sectional explanatory power of model-forecast averages 44% and reaches as high as 91%. Explanatory power is even stronger for corporate bonds, with an average cross-sectional R^2 of 64%.

Collectively, these results show that the proposed structural model provides a coherent and useful characterization of risk and expected returns in equity and corporate bond markets, with strong empirical performance across firms, industries, and the aggregate market.

Our study is related to the corporate bond asset pricing literature, which began with efforts to identify factors that explain the cross-section. A seminal contribution is Fama and French (1993). Subsequent advances emphasize the role of liquidity risk (Lin, Wang, and Wu, 2011), intermediary risk (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017), as well as characteristics such as value and momentum. See Huang and Shi (2021) for a comprehensive survey. The literature has since evolved along multiple dimensions. Dickerson, Mueller, and Robotti (2023) demonstrate that the corporate bond market factor (denoted CAPMB) is not dominated by other frequentist models — however, the CAPMB itself, is shown to be a poor model to describe the cross-section of bond returns. Another line of research applies instrumented principal component techniques, as in Kelly, Palhares, and Pruitt (2023) and regressed principal component analyses (Chen, Roussanov, Wang, and Zou, 2024), to study the pricing of latent factors. Our contribution is to document that aggregate variance risk, which has received limited attention to date, appears to be an important source of priced risk in corporate bond returns.[8]

Our paper is closely related to recent papers that have shown that models that work well for the pricing of risk in equity markets can help explain corporate bond spreads. For example Chen, Collin-Dufresne, and Goldstein (2009) find that the time-variation in asset Sharpe ratios inherent in a model of habit formation helps resolve much of the overpricing of corporate bonds that has plagued the literature since Merton (1974). Other important contributions to the joint modeling of equity and credit markets include Bhamra, Kuehn, and Strebulaev (2010b), Chen (2010), and Kung and Schmid (2015). We contribute to this literature by showing that a credit risk model incorporating aggregate variance risk—a key driver of time-variation in risk premia and Sharpe ratios—provides a strong fit to the time-series dynamics of risk and return in both equity and credit markets.

Another related strand of the literature seeks to understand how closely related equity and debt markets are (see e.g. Schaefer and Strebulaev (2008) and Choi and Kim (2018)) by using the relationship between equity and debt returns implied by the Merton (1974) model. Other papers in this vein include Campello, Chen, and Zhang (2008) who use bond yield spreads translated via the Merton (1974) model to compute ex ante equity returns. In related work, Friewald, Wagner, and Zechner (2014) use term structures of default swap prices and a structural credit model to estimate conditional expected equity returns. Culp, Nozawa, and Veronesi (2018) use the information in index options to construct implied credit spread measures.

We differ from this line of work in at least two important ways. First, we estimate our model jointly on equity and credit markets, rather than taking pricing in one market as given to explain pricing in the other. Second, our model allows for an endogenous and theoretically implied factor structure of corporate claims accounting for the impact of aggregate variance risk. This has a substantial economic and quantitative impact on the functional form of the relationship between equity and credit prices, returns, and risk measures. Although not the primary focus of our study, the Sharpe ratio implied by our model tends to be significantly higher for bonds than for stocks in the presence of priced variance risk.[9] In turn, this suggests

[8] This is consistent with the work of Campbell and Taksler (2003), McQuade (2018), and Du et al. (2019).

[9] This echoes findings by Saita (2005), who document that Sharpe ratios for portfolios of corporate bonds are significantly larger than those for a well-diversified stock index such as the S&P 500. This disparity between equity and corporate bond Sharpe ratios is also consistent with Campbell, Hilscher, and Szilagyi (2008), who

caution when using prices in one market to infer pricing in the other, since shared systematic sources of risk may impact prices differently across markets.

The remainder of the paper is organized as follows. Section 1 presents the model, while Section 2 discusses its implications for the factor structure of corporate claim returns. Section 3 describes the data. Section 4 presents the market-level analysis, including model estimation and empirical findings. Section 5 examines the robustness of our results at the industry level. Section 6 presents various firm-level tests. Finally, Section 7 concludes.

1 Model

In this section, we describe a structural credit risk model that enables consistent pricing of equities and corporate bonds. We begin by introducing the asset dynamics of individual firms, the underlying sources of systematic risk, and the economy's stochastic discount factor. This is followed by the pricing of corporate securities. We then construct equity and credit portfolios. We analyze the factor structure of these portfolios in our model in Section 2.

1.1 Asset and variance dynamics

We consider a cross-section of firms indexed by j, whose unlevered asset dynamics under the physical measure $\mathbb{P}$ follow a one-factor structure driven by an aggregate asset factor M_t and idiosyncratic shocks:

$$\frac{dA_t^j}{A_t^j} = (r-q)\,dt + \beta_j\left(\frac{dM_t}{M_t} - r\,dt\right) + \sigma_j dW_t^j, \tag{1}$$

where r is the constant risk-free rate, dW_t^j is a standard Brownian motion representing idiosyncratic risk, and σ_j is the constant volatility parameter for diffusive idiosyncratic risk. We use q to denote the payout rate, which we assume to be identical across all firms.

Following recent advances in the credit risk literature (see, e.g., Du et al., 2019; Doshi et al., 2024; Collin-Dufresne et al., 2024), the dynamics of the aggregate (unlevered) asset factor M_t and its stochastic variance V_t can be characterized by the following equations under $\mathbb{P}$:

$$\frac{dM_t}{M_t} = \mu_t dt + \sqrt{V_t}dW_t^M \tag{2}$$

$$dV_t = \kappa(\theta - V_t)dt + \delta\sqrt{V_t}dW_t^V, \tag{3}$$

find that equity returns are lower for distressed firms.

where μ_t is the expected return on the unlevered "market". The systematic diffusive variance V_t follows a square-root process where κ, θ, and δ represent the mean-reversion speed, long-run mean, and volatility of variance, respectively. To model the correlation between aggregate asset return and variance shocks, we assume that $dW_t^M = \rho dW_t^V + \sqrt{1-\rho^2} dW_t^{M\perp V}$ where dW_t^V and $dW_t^{M\perp V}$ are two mutually independent Brownian motions. When $\rho < 0$, aggregate asset variance increases when aggregate asset returns are low. This case implies a negative skewness in the distribution of unlevered market returns, consistent with empirical evidence.[10]

Given the firm-level unlevered asset and the market dynamics, a key condition is required to ensure that the aggregation of individual firm assets replicates the dynamics of the unlevered market. Specifically, the number of firms in the market, N_M, must be sufficiently large such that idiosyncratic shocks diversify away and the average firm-level asset beta (β_j) across firms converges to 1.[11]

We assume the absence of arbitrage, and hence the existence of a stochastic discount factor (SDF), which allows us to price firms' financial claims. Following the literature, we assume that the SDF is exponentially affine in aggregate risks:

$$\frac{d\phi_t}{\phi_t} = -r dt - \xi_{M\perp V}\sqrt{V_t} dW_t^{M\perp V} - \xi_V \sqrt{V_t} dW_t^V, \tag{4}$$

where $\xi_{M\perp V}$ and ξ_V represent the market prices of diffusive asset-specific and variance risk, respectively. Note that idiosyncratic risks at the firm level are not priced in this framework by construction. Appendix A discusses the risk-neutralization of the model and presents the solution for the unlevered market and variance risk premia.

1.2 Pricing firm-level contingent claims

Following Leland (1994), we assume that each firm issues a consol bond. Firm j declares bankruptcy when its asset value falls below a fixed threshold. In the model, the timing of the firm's default τ_j corresponds to the first time at which the asset value A_t^j in equation (1) hits the default barrier A_D^j: $\tau_j = \inf\{s \geq t | A_s^j \leq A_D^j\}$.

Prices of a firm's securities and contingent claims depend on the risk-neutral distribution of τ_j and are a function of two key quantities: (i) the present value of a dollar received at default

[10]For discussions on the presence of negative skewness in the distribution of systematic risks, see Berger et al. (2020), among others.

[11]Moreover, any income received from holding the assets q must be continuously reinvested.

$P_D(A_t^j, V_t) = \mathbb{E}_t^{\mathbb{Q}}[e^{-r(\tau_j - t)}]$ and (ii) the cumulative risk-neutral default probability $G(A_t^j, V_t, T) = \mathbb{E}_t^{\mathbb{Q}}[\mathbb{1}_{\tau_j \leq T}]$ over the next T years. Using these two quantities, we are able to price any security issued by the firm. The firm's debt value $B(A_t^j, V_t)$ is the present value of future coupon payments plus the recovery value of the firm upon default:

$$B(A_t^j, V_t) = \frac{c^j}{r} \cdot \big(1 - P_D(A_t^j, V_t)\big) + (1-\alpha) \cdot A_D^j \cdot P_D(A_t^j, V_t), \tag{5}$$

where c_j is the coupon and α is the financial distress cost. The firm's equity is given by:

$$S(A_t^j, V_t) = A_t^j - \frac{(1-\zeta)c^j}{r} \cdot \big(1 - P_D(A_t^j, V_t)\big) - A_D^j \cdot P_D(A_t^j, V_t), \tag{6}$$

where ζ denotes the corporate tax rate. Both corporate tax rate and financial distress cost are assumed to be identical across all firms.

Our empirical analysis also requires us to compute model-implied credit spreads for a given horizon T, $CS_T(A_t^j, V_t)$, which depends on the cumulative risk-neutral default probability over the next T years. Appendix B provides the details.

1.3 Corporate security portfolios and representative firms

So far, we have specified the dynamics of individual firms' asset values and outlined the valuation of their corporate securities. Our objective is to characterize the joint return dynamics of the equity and corporate bond market portfolios, as well as those of the representative firm for the overall market and for a given industry.

We begin by defining the value of the market portfolio of stocks and corporate bonds. Consider the equally weighted market portfolio M_f composed of corporate security f with N_M constituents:

$$M_f(A_t^1, ..., A_t^{N_M}, V_t) \equiv \frac{1}{N_M} \sum_j f(A_t^j, V_t), \tag{7}$$

where f is defined by equation (5) for corporate bonds and by equation (6) for stocks. In our implementation, the "market" is defined by the constituents of the S&P500 with traded corporate bonds. Modeling the dynamics of such portfolio would require tracking $N_M + 1$ state variables over time: the N_M firm-specific asset values A_t^j and the systematic V_t.

To reduce this dimensionality, we follow the literature and approximate the market portfolio with a homogeneous pool of ex-ante identical firms (see, e.g., Vasicek, 2002; Collin-Dufresne et al., 2024). Accordingly, we define a representative firm for the overall market, denoted by superscript R, whose asset dynamics follow equation (1). The homogeneity assumption implies that $A_t^j = A_t^R$ and $\{\beta_j, \sigma_j, c^j, A_D^j\} = \{\beta_R, \sigma_R, c^R, A_D^R\}$ for all j. Note that we normalize the asset beta exposure of this representative firm β_R to 1. Under the homogeneity assumption, the market portfolio simplifies to $M_{f,t} = \frac{1}{N_M}\sum_{j=1}^{N_M} f(A_t^R, V_t) = f(A_t^R, V_t)$. This simplification reduces the state space to two variables: the representative asset value A_t^R and the systematic variance V_t. It is important to distinguish between levels and dynamics. While $M_{f,t}$ and $f(A_t^R, V_t)$ are equal in level, their dynamics differ, as $f(A_t^R, V_t)$ depends on idiosyncratic risk whereas $M_{f,t}$ does not. To illustrate this point, consider the unlevered case where $f(A_t^R, V_t) = A_t^R$. By homogeneity, we have $M_t = \frac{1}{N_M}\sum_{j=1}^{N_M} A_t^R = A_t^R$ even though the dynamics of A_t^R (as given in equation (1) with $j = R$) include idiosyncratic shocks, while those of the unlevered market M_t (in equation (2)) do not. The same logic applies in the levered case when comparing $M_{f,t}$ and $f(A_t^R, V_t)$. Proposition 1 in the next section clarifies this point.

Some of our industry-level analyses require us to specify the dynamics of the representative firm for each industry. Similarly to the overall market, we hypothesize the existence of a representative firm for each industry. For notational convenience, we use the same index "R" for the representative firms for the overall market and those for individual industries, although their dynamics may differ. The industry-specific representative firm satisfies $A_t^j = A_t^R$ and $\{\beta_j, \sigma_j, c^j, A_D^j\} = \{\beta_R, \sigma_R, c^R, A_D^R\}$ for all j in a given industry. By homogeneity, an industry portfolio composed of N_I claims on these representative firms also satisfies $I_{f,t} = \frac{1}{N_I}\sum_{j=1}^{N_I} f(A_t^R, V_t) = f(A_t^R, V_t)$. In contrast to the market case, we do not assume that idiosyncratic risk diversifies away within industry portfolios.

While the homogeneity assumption is used for the market- and industry-level analysis, we allow for heterogeneous firm asset dynamics in our firm-level empirical tests.

2 Model Properties

While a substantial literature in asset pricing studies stock and corporate bond returns using factor models, the selection of factors often remains ad hoc. Structural credit risk models, by contrast, discipline return predictions across both asset classes by linking expected returns and their joint dynamics to assumptions about corporate asset dynamics. This insight, on the other hand, received limited attention.[12]

In the classical Merton (1974) framework, all securities written on a firm's assets—whether stocks or corporate bonds—are exposed to the same underlying source of risk. Consequently, excess returns across these claims admit a one-factor structure and are fully determined by their sensitivities to a single aggregate asset return factor. In contrast, our model incorporates both systematic asset return and asset variance risks. This richer framework has significant implications for the joint dynamics of equity and corporate bond returns.[13]

As a first step, Proposition 1 characterizes the joint factor structure embedded in our framework.

Proposition 1. *Consider a representative firm "R", and its contingent claims* $f_t \equiv f(A_t^R, V_t)$, *defined by equation (6) for a stock or by equation (5) for a bond, and whose value is determined by the dynamics (1)-(3) and the SDF in (4). Furthermore, consider the market portfolio,* $M_{f,t}$, *of these claims. Then, an application of Itô's lemma combined with no-arbitrage restrictions implies the following conditional factor structure*

$$\frac{df_t}{f_t} = rdt + \beta_{f,t}^A\left(\frac{dM_t}{M_t} - rdt\right) + \beta_{f,t}^V\left(dV_t - \mathbb{E}_t^{\mathbb{Q}}\left[dV_t\right]\right) + d\epsilon_{f,t} \tag{8}$$

$$\frac{dM_{f,t}}{M_{f,t}} = rdt + \beta_{M_f,t}^A\left(\frac{dM_t}{M_t} - rdt\right) + \beta_{M_f,t}^V\left(dV_t - \mathbb{E}_t^{\mathbb{Q}}\left[dV_t\right]\right), \tag{9}$$

where $\mathbb{E}_t^{\mathbb{Q}}[\cdot]$ *denotes the risk-neutral expectation and the factor exposures satisfy* $\beta_{f,t}^A \equiv \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R$ *where* $\beta_R = 1$ *for the market-level representative firm,* $\beta_{f,t}^V \equiv \frac{\partial f_t}{\partial V_t}\frac{1}{f_t}$, *and* $d\epsilon_{f,t} = \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\sigma_R dW_t^R$ *denotes the idiosyncratic risk of claim* f_t *such that* $\mathbb{E}_t^{\mathbb{P}}[d\epsilon_{f,t}] = 0$. *Moreover,* $\beta_{M_f,t}^A = \frac{\partial M_{f,t}}{\partial M_t}\frac{M_t}{M_{f,t}}$ *and* $\beta_{M_f,t}^V = \frac{\partial M_{f,t}}{\partial V_t}\frac{1}{M_{f,t}}$.

Proof. See Appendix C. □

While a firm's assets in equation (1) admit an unconditional one-factor model, the cross-section of excess returns on corporate claims exhibits a two-factor structure, with factors corresponding to aggregate asset risk and asset variance risk. Importantly, the factor exposures of a given corporate claim, whether stock or bond, are highly conditional, as they depend on the levels of the state variables A_t^R and V_t. These state variables affect the valuation of the

[12] To date, these models have mostly been used to predict corporate bond prices and credit spreads. Recently, they have been extended to analyze option prices. Few have used them to relate returns across the asset classes (exceptions are cited in the introduction).

[13] For empirical evidence on the role of systematic variance risk in the valuation of equities and corporate bonds, see, among others, Ang et al., 2006, Bollerslev et al., 2009, and Du et al., 2019.

corporate claim f_t and, in turn, determine its sensitivities to the underlying risk factors, as captured by the time-varying loadings $\beta^A_{f,t}$ and $\beta^V_{f,t}$ (or $\beta^A_{M_f,t}$ and $\beta^V_{M_f,t}$ in the market portfolio case).

Due to fundamental differences in their payoff structures and recovery characteristics in the event of default, debt and equity exhibit distinct sensitivities to changes in underlying state variables. As a result, these asset classes load differently on the same underlying factor. To illustrate this, we use the model to generate predictions of stock and corporate bond market return elasticities to aggregate asset and variance risk. For this exercise, we use the estimated structural parameters from Table 2, fixing V_t at $\hat{\theta}$ and solving for the representative firm asset value that matches three levels of credit spread: 0.80% (low credit risk), 1.80% (medium), and 2.80% (high). Panels A to C of Figure 1 report market portfolio elasticities to asset and variance risk, expressed as $\beta^A_{M_f,t}\sqrt{V_t}$ and $\beta^V_{M_f,t}\delta\sqrt{V_t}$, measuring the annualized percentage return change from a one-standard-deviation shock to M_t or V_t. Left panels display results for stocks; right panels for bonds.

Figure 1 [about here]

The top two panels show that both stocks and corporate bonds have positive exposure to aggregate asset risk: increases in the firm's asset value raise the value of both claims. Because equity is a junior claim relative to debt, it offers greater upside and embedded leverage, which explains why $\beta^A_{M_S} > \beta^A_{M_B}$. The figure also highlights that asset risk elasticities for both portfolios grow with default risk, underscoring the conditional nature of exposures to economic conditions.

In models without tax shields or bankruptcy costs, such as Merton (1974), the exposures of equity and debt valuation to variance risk are equal in magnitude and opposite in sign (i.e., $\frac{\partial S_t}{\partial V_t} = -\frac{\partial B_t}{\partial V_t}$).[14] An intriguing implication of our model is that both price and return exposures of corporate bonds to aggregate variance risk are larger in absolute value than those of the stock market (see Panels C and D). This difference arises from the presence of tax shields and bankruptcy costs, both of which affect how stock and debt return respond to systematic variance.[15]

[14] This result is a direct consequence of the accounting equality, $A^R_t = B(A^R_t) + S(A^R_t)$, and the fact that in such models, firm value has no exposure to systematic variance (i.e., $\partial A^R_t/\partial V_t = 0$).

[15] Merton (1974) was extended to incorporate taxes and bankruptcy costs by Brennan and Schwartz (1978) and Leland (1994). We have qualitatively confirmed the exposure patterns depicted in Figure 1 within the Leland (1994) framework. Note that in the Leland (1994) model with "unprotected" debt, the default boundary also depends on the tax rate. A higher tax rate translates into more patient shareholders and, thus, lower distress risk, as well as lower bond exposure to variance risk in absolute terms.

When the likelihood of default increases with systematic variance (i.e., $\partial P_D(A_t^R, V_t)/\partial V_t > 0$), the presence of a tax shield reduces equity exposure to variance risk, as

$$\beta_{M_S}^V = \beta_{M_S}^V\Big|_{\zeta=0} - \frac{\zeta c^R}{r M_{S,t}} \frac{\partial P_D(A_t^R, V_t)}{\partial V_t}, \tag{10}$$

where $\beta_{M_S}^V\Big|_{\zeta=0}$ denotes the stock index exposure without tax shield of debt. Intuitively, the debt tax shield increases the levered firm value, providing a hedge against variance risk and thereby reducing equityholders' variance exposure.[16] Conversely, bankruptcy costs amplify the downside risk borne by debtholders, increasing their exposure to variance risk:

$$\beta_{M_B}^V = \beta_{M_B}^V\Big|_{\alpha=0} - \frac{\alpha A_D^R}{M_{B,t}} \frac{\partial P_D(A_t^R, V_t)}{\partial V_t}, \tag{11}$$

where $\beta_{M_B}^V\Big|_{\alpha=0}$ denotes the bond index exposure without bankruptcy cost. Economically, Panel C shows that the tax shield reduces the stock market's elasticity to variance risk by nearly half, regardless of the level of credit risk. For bonds, Panel D indicates that bankruptcy costs more than double the magnitude of their negative variance exposures.

To understand how the conditional risk premium for corporate claims decomposes into compensation for different sources of systematic risk, consider the following proposition.

Proposition 2. *Consider the state variable and SDF dynamics specified in equations (1)–(3) and (4). Under these assumptions, the expected excess return (risk premium) on any market- or industry-level portfolio of contingent claims—or on an individual firm-level contingent claim issued by the corresponding representative firm—admits a two-factor representation, we have*

$$\mathbb{E}_t^{\mathbb{P}}\left[\frac{dM_{f,t}}{M_{f,t}}\right] - \mathbb{E}_t^{\mathbb{Q}}\left[\frac{dM_{f,t}}{M_{f,t}}\right] \equiv \lambda_{M_f,t}dt = \left(\beta_{M_f,t}^A \cdot \lambda_{M,t} + \beta_{M_f,t}^V \cdot \lambda_{V,t}\right) dt \tag{12}$$

$$\mathbb{E}_t^{\mathbb{P}}\left[\frac{dI_{f,t}}{I_{f,t}}\right] - \mathbb{E}_t^{\mathbb{Q}}\left[\frac{dI_{f,t}}{I_{f,t}}\right] \equiv \lambda_{I_f,t}dt = \left(\beta_{I_f,t}^A \cdot \lambda_{M,t} + \beta_{I_f,t}^V \cdot \lambda_{V,t}\right) dt, \tag{13}$$

$$\mathbb{E}_t^{\mathbb{P}}\left[\frac{df_t}{f_t}\right] - \mathbb{E}_t^{\mathbb{Q}}\left[\frac{df_t}{f_t}\right] \equiv \lambda_{f,t}dt = \left(\beta_{f,t}^A \cdot \lambda_{M,t} + \beta_{f,t}^V \cdot \lambda_{V,t}\right) dt, \tag{14}$$

where, as shown in Appendix A, the risk premia for the two unlevered factors are $\lambda_{M,t} = \mu_t - r$ and $\lambda_{V,t} = \delta\xi_V V_t$, respectively. Moreover, $\beta_{I_f,t}^A = \frac{\partial I_{f,t}}{\partial M_t}\frac{M_t}{I_{f,t}}\beta_R$ and $\beta_{I_f,t}^V = \frac{\partial I_{f,t}}{\partial V_t}\frac{1}{I_{f,t}}$.

Proof. See Appendix C. □

This result provides insights into the key determinants of the conditional risk premium across equities and corporate bonds. Since systematic asset risk tends to be pro-cyclical while

[16] In our model, firm value is given by $A_t^R + \frac{\zeta c^R}{r} \cdot \left(1 - P_D(A_t^R, V_t)\right) - \alpha \cdot A_D^R \cdot P_D(A_t^R, V_t)$.

asset variance risk is counter-cyclical, the corresponding conditional risk premia usually satisfy $\lambda_{M,t} > 0$ and $\lambda_{V,t} < 0$, respectively.[17] Given that both stock and bond values increase with the value of a firm's assets, we have: $\beta^A_{M_S,t} > 0$ and $\beta^A_{M_B,t} > 0$. However, as discussed above, a change in asset variance affects stock and bond valuations in opposite directions since $\beta^V_{M_S,t} > 0$ and $\beta^V_{M_B,t} < 0$. A direct implication of this result is that the asset variance risk premium tends to reduce the conditional risk premium on equities, while it increases the corresponding premium on corporate bonds.

Figure 2 [about here]

Panels A and B of Figure 2 report the (annualized) risk premium for stock and corporate bond markets, and its decomposition into asset and variance risk components: $\beta^A_{M_f,t}\lambda_{M,t}$ and $\beta^V_{M_f,t}\lambda_{V,t}$. The variance risk premium for stocks is small and negative, while for bonds, it is economically significant—especially at low credit risk levels.

The final proposition presents the model's implications for the conditional volatility of a contingent claim position, both for the market portfolio and for the representative firm.

Proposition 3. *Consider the state variable and SDF dynamics specified in equations (1)–(3) and (4). Then, the conditional return volatility on a corporate security position f_t denoted by $\sigma^2_{f,t}$ and of the market portfolio of such security, $\sigma^2_{M_f,t}$, are given by*

$$\sigma^2_{f,t} = \left(\left(\beta^A_{f,t}\right)^2 + \left(\beta^V_{f,t}\cdot\delta\right)^2 + 2\rho\delta\cdot\beta^A_{f,t}\cdot\beta^V_{f,t}\right)\cdot V_t + \left(\frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t}\right)^2\cdot\sigma^2_R \tag{15}$$

$$\sigma^2_{M_f,t} = \left(\left(\beta^A_{M_f,t}\right)^2 + \left(\beta^V_{M_f,t}\cdot\delta\right)^2 + 2\rho\delta\cdot\beta^A_{M_f,t}\cdot\beta^V_{M_f,t}\right)\cdot V_t. \tag{16}$$

Proof. See Appendix C. □

Panels C and D of Figure 2 show the total (annualized) variance of stock and corporate bond markets, and its decomposition. Note that the variance risk component of a given portfolio is calculated as $((\beta^V_{M_f,t}\cdot\delta)^2 + 2\rho\delta\cdot\beta^A_{M_f,t}\cdot\beta^V_{M_f,t})\cdot V_t$, which explains why this component is slightly negative for equities as $\rho\beta^A_{M_S,t}\beta^V_{M_S,t} < 0$. Consistent with previous results, we see that stock risk is primarily driven by asset uncertainty, whereas variance risk contributes significantly to bond market volatility.

[17] These sign restrictions align with our subsequent empirical findings and a broad body of empirical evidence on the risk compensation for the equity/bond counterparts of these unlevered/asset factors in the stock and credit markets.

To summarize, three key model implications stand out. First, a one-factor model for unlevered firm assets, as in CAPM, implies a two-factor structure for stock and corporate bond markets. Second, factor exposures depend on each claim valuation and are, therefore, highly conditional in nature. In addition, differences in cash flow contingencies cause these asset classes to have distinct exposures to the same risk factors. Third, variance risk and its compensation play a more significant role for bonds than for equities.

We now proceed to the empirical analysis of the model's ability to capture the joint dynamics of risk and return for equities and corporate bonds.

3 Data

In this section, we first introduce the datasets that form the basis of our study. We then describe the construction of key variables used in the subsequent empirical analysis.

3.1 Data sources

We construct our sample using the constituents of the corporate bond dataset from the Intercontinental Exchange (ICE) indices, covering the period from January 1997 to December 2022. Specifically, we include bonds that are part of the Bank of America High Yield Index (H0A0) and the Investment Grade Index (C0A0).[18] Additional bond characteristics are obtained from the Mergent/LSEG Fixed Income Securities Database (FISD), which we match to the ICE data using bond CUSIP identifiers. We apply a series of filters to exclude bonds that (i) are not listed or traded on the U.S. public market, (ii) are structured notes, mortgage-backed, asset-backed, agency-backed, or equity-linked securities, (iii) are convertible, (iv) have floating coupon rates, or (v) have less than one year to maturity. We then merge the corporate bond data with CRSP's monthly S&P 500 equity data and Compustat using the Wharton Research Data Services (WRDS) Bond Linker and historical NCUSIP identifiers, at both the firm and issue levels. Our final sample includes approximately 764 S&P 500 firms with both traded stocks and outstanding corporate bonds.

[18]The ICE data has been used in a range of studies which have a focus on credit risk modeling and asset pricing in general, including Schaefer and Strebulaev (2008), Feldhütter and Schaefer (2018), Kelly et al. (2023) and van Binsbergen et al. (2025).

3.2 Variable definitions

Corporate bond and stock returns: The total return for corporate bond i of firm j in month t is computed as,

$$r_{B,i,j,t} = \frac{B_{i,j,t} + AI_{i,j,t} + C_{i,j,t}}{B_{i,j,t-1} + AI_{i,j,t-1}} - 1,$$

where $B_{i,j,t}$ is the clean price of bond j, $AI_{i,j,t}$ is the accrued interest, and $C_{i,j,t}$ is the coupon payment, if any. Our analysis relies on duration-hedged (DH) corporate bond returns, $R_{B,i,j,t}$, defined as the total bond return minus the return on a portfolio of duration-matched U.S. Treasuries.[19] Duration hedging addresses two concerns: it removes spurious predictability from term structure fluctuations and aligns the data with the model's assumption of a constant risk-free rate. We compute firm-level DH returns, denoted $R_{B,j,t}$, as the amount outstanding-weighted average of bond-level DH returns.[20] We compute stock returns as $r_{S,j,t} = \frac{S_{j,t}+D_{j,t}}{S_{j,t-1}} - 1$, where $S_{j,t}$ is the stock price of firm j and $D_{j,t}$ is the dividend paid during month t (if any). Firm j's stock excess returns, $R_{S,j,t}$, are computed relative to the one-month Treasury bill rate. For a given asset class, the market corresponds to the equally-weighted average of the excess returns of its constituents. Using an equal-weighting scheme ensures consistency with our model and facilitates comparability across the two asset classes. We denote the excess return on the DH corporate bond market ($f = B$) and the stock market ($f = S$) by R_{M_f}. Industry portfolio returns and averages of firm-level variables (e.g., credit spread, leverage, total debt) are computed using equal weights to ensure consistency across all measures.

Representative firm credit spread and leverage: For each firm, we compute a 10-year credit spread by interpolating the available credit spreads across different maturities for each month. We require at least two observations with a minimum maturity difference of two years. We define leverage as the ratio of total liabilities (Compustat item *ltq*) to the sum of total liabilities and market capitalization from CRSP. To obtain a monthly leverage measure, we roll forward the quarterly *ltq* values. Finally, we compute the equally weighted average of the firm-level 10-year credit spreads and leverage for each month, both at the market level and

[19]We follow Andreani et al. (2024) to compute at each month t, for each bond i, portfolios of duration-matched U.S. Treasury portfolios using bond effective duration. A detailed description of the duration-matching procedure is documented in Section IA.3

[20]The use of firm-level average bond return is common practice in the corporate bond literature and allows us to align the empirical analysis with the theoretical framework, in which each firm has a single outstanding bond. See e.g., Choi (2013); Choi and Richardson (2016).

within each industry, to obtain representative firm-level measures. We denote the market-wide representative firm's measures by CS_{10}^m and Lev^m. Analogous industry-level quantities are defined using the subscript I instead of m.

Market and representative firm stock and bond conditional volatilities: For both asset classes and levels of aggregation, monthly conditional volatilities are obtained by fitting an NGARCH model with Student-t innovations to the time series of stock excess returns and bond DH returns. Market-level conditional volatility measures are computed using market returns. For the representative firm, we first estimate conditional volatilities at the firm level, then compute equally weighted averages across firms at the market or industry level.[21] We denote by $\sigma_{M_S}^m$ the aggregate stock market volatility, by σ_S^m the stock volatility of the (market-wide) representative firm, by $\sigma_{M_B}^m$ the volatility of the DH corporate bond market, and by σ_B^m the volatility of the representative firm's DH bond return. Industry-level counterparts are defined by replacing the subscript m with I.

Remaining variables: We consider the following additional variables. Building on Martin (2017), we use the squared VIX index ($SVIX$) to benchmark our model's return predictions and predictive performance for stocks. One of the parameters of our model is the default barrier, which we define as a function of total debt, calculated as the sum of Compustat items *dlcq* and *dlttq*. We roll forward total debt to obtain a monthly measure for each firm, and then compute the average (across firms and then over time) at the market level or industry level.

4 Equity and Credit Market Analysis

This section presents our market-level empirical findings. We first discuss summary statistics. We then elaborate on our estimation strategy that aims to identify the dynamics of systematic risks and that of the representative firm for the overall market. We discuss parameter estimates before exploring the model's ability to capture the empirical patterns characterizing corporate bond and stock returns and risks.

[21] For the firm level estimation, we require at least 24 consecutive monthly observations.

4.1 Summary statistics

Table 1 [about here]

Our sample includes approximately 338 firms per month, spanning 312 monthly observations from January 1997 to December 2022. Table 1 presents descriptive statistics including the time-series mean, standard deviation, minimum, maximum, skewness, and kurtosis of key measures for both the market (S&P 500) and its representative firm, the average firm of the S&P 500. The mean excess return of the stock market is 9.57%, more than five times higher than that of DH bonds, which stands at 1.81%. Stock market returns are also significantly more volatile, with an average GARCH volatility of 15.23%, compared to just 3.51% for the DH bond market. DH bond returns exhibit more negative skewness and significantly higher kurtosis than stock market returns. When comparing the average market-level volatility to that of the representative firm, the benefits of diversification are notably greater for stocks than for DH bonds. For example, while the volatility of a representative individual stock is 29.25%, the stock market portfolio exhibits a volatility of just 15.23%, implying a 47.93% reduction through diversification. In contrast, diversification within the DH bond market yields a smaller reduction of 27.78%. The average 10-year credit spread, 179.66 bps, is comparable in magnitude to the average realized return on the DH bond market portfolio. On average, firms in the S&P 500 exhibit a leverage ratio of 0.45 and hold approximately 18.72 billion in debt.

4.2 Estimation

In total, the model features 13 structural parameters and two latent variables. To reduce the dimensionality of the parameter space, we fix the values of several parameters following Feldhütter and Schaefer (2018) and Du et al. (2019), among others. Specifically, we set the bankruptcy cost α to 50%, the corporate tax rate ζ to 20%, and the bondholders' recovery rate R to $1 - \alpha = 50\%$ when computing credit spreads (see Appendix B). The risk-free rate is set to the sample average of the 1-month T-Bill rate, which is 1.87%, and the asset payout ratio is fixed at 2%. We set the default barrier to two-thirds of the sample average of total debt (expressed in billions) from Table 1.[22] Moreover, we normalize β_R to 1 in the unlevered asset dynamics of the firm representative the overall market. We relax this restriction later for the industry analysis.

[22]Using 2/3 of total debt is consistent with Davydenko (2012).

Panel A of Table 2 summarizes and reports our calibration choices.

Table 2 [about here]

This leaves us with 8 structural parameters $\Theta \equiv \{\kappa, \theta, \delta, \rho, \xi_{M\perp V}, \xi_V, \sigma_R, c^R\}$ to estimate and two latent variables (A_t^R, V_t) to filter. To do so, we adopt a monthly observation frequency and assume that market-level empirical measures of the 10-year credit spread ($CS_{10,t}^m$) and of the physical conditional stock market volatility ($\sigma_{M_S,t}^m$) are accurately observed (see, e.g., Aït-Sahalia and Kimmel, 2010; Doshi et al., 2024). We can then filter out $\hat{A}_t^R$ and $\hat{V}_t$ from $CS_{10,t}^m$ and $\sigma_{M_S,t}^m$, monthly, by solving the following two equations:

$$\text{10-year credit spread:} \quad CS_{10,t}^m = \quad CS_{10}(\hat{A}_t^R, \hat{V}_t; \Theta) \tag{17}$$

$$\text{Stock market vol.:} \quad \sigma_{M_S,t}^m = \quad \sqrt{\sigma_{M_S}^2(\hat{A}_t^r, \hat{V}_t; \Theta)}, \tag{18}$$

where $CS_T(\cdot)$ and $\sigma_{M_S}^2(\cdot)$ are the model conditional credit spread and market volatility functions.

To capture the evolution of equity and credit risk at both the firm and market levels, we use a set of four additional observables as input to the estimation: leverage, volatility measures for the representative firm's stock and DH bond returns, and the volatility of the aggregate DH corporate bond market.

The model likelihood is constructed over the six variables, the 10-year credit spread ($CS_{10,t}^m$) and aggregate stock market volatility ($\sigma_{M_S,t}^m$), which are treated as accurately observed. The remaining four variables are assumed to be measured with error: representative firm equity volatility ($\sigma_{S,t}^m$), DH corporate bond market volatility ($\sigma_{M_B,t}^m$), representative firm DH bond return volatility ($\sigma_{B,t}^m$), and the representative firm leverage (Lev_t^m). Our estimation strategy postulates that the relative pricing errors on the remaining four variables are observed with Gaussian errors such that

$$\text{Rep. firm stock vol.:} \left(\sigma_{S,t}^m - \sigma_S(\hat{A}_t^R, \hat{V}_t; \Theta)\right) \cdot \left(\sigma_{S,t}^m\right)^{-1} = \quad e_t^S \tag{19}$$

$$\text{DH Corp. bond market vol.:} \left(\sigma_{M_B,t}^m - \sigma_{M_B}(\hat{A}_t^R, \hat{V}_t; \Theta)\right) \cdot \left(\sigma_{M_B,t}^m\right)^{-1} = \quad e_t^{M_B} \tag{20}$$

$$\text{Rep. firm DH corp. bond vol.:} \left(\sigma_{B,t}^m - \sigma_B(\hat{A}_t^R, \hat{V}_t; \Theta)\right) \cdot \left(\sigma_{B,t}^m\right)^{-1} = \quad e_t^B \tag{21}$$

$$\text{Rep. firm Lev.:} \left(Lev_t^m - Lev(\hat{A}_t^R, \hat{V}_t; \Theta)\right) \cdot (Lev_t^m)^{-1} = \quad e_t^{Lev}, \tag{22}$$

where $\mathbf{e}_t \sim N(0, \Sigma)$ with $\mathbf{e}_t$ denoting the 4 by 1 vector of errors. The model variables are discussed in Sections 1 and 2, and their computations are presented in the Internet Appendix IA.1.

On the one hand, the level and dynamics of credit spreads, leverage, and volatilities embed relevant information about the model's $\mathbb{P}$- and $\mathbb{Q}$-dynamics. On the other hand, the joint use of representative firm stock and bond volatilities together with their market counterparts provides insights into the extent of diversification benefits within each market, thereby aiding the identification of systematic and idiosyncratic sources of risk.

We estimate Θ by maximizing the log-likelihood function, which is given by

$$\log \mathcal{L}(\Theta) = \sum_{t=2}^{T} \log \mathbb{P}\left(Y_t \mid Y_{t-1}; \Theta\right),$$

where $Y_t = \{CS^m_{10,t}, \sigma^m_{M_S,t}, \sigma^m_{S,t}, \sigma^m_{M_B,t}, \sigma^m_{B,t}, Lev^m_t\}$ is the vector of observables on month t. Note that the distribution of the filtered state variables and the mapping from $\{\hat{A}^R_t, \hat{V}_t\}$ to the vector of observables Y_t are taken into account when computing $\mathbb{P}\left(Y_t \mid Y_{t-1}; \Theta\right)$. Details about the construction and computation of the likelihood function in our framework are provided in Appendix D.

4.3 Parameter estimates

Panel A of Table 2 reports the estimates of the structural parameters governing systematic risks and the representative firm in the S&P 500. Robust standard errors are shown in brackets and are computed using the Huber sandwich estimator.

The first three parameters characterize the dynamics of the systematic variance process V_t. The mean-reversion speed $\hat{\kappa} = 2.82$ implies a monthly persistence of $e^{-2.82/12} \approx 0.79$, consistent with empirical estimates of variance processes for equity indices.[23] The long-run mean of variance, $\hat{\theta} = 0.72\%$, corresponds to an annualized standard deviation of unlevered market returns of approximately 8.49%. The volatility of variance parameter, $\hat{\delta} = 10.19\%$, governs the time-variation in V_t and in the aggregate variance risk premium. The estimated correlation between asset returns and variance shocks, $\hat{\rho} = -30.61\%$, is statistically significant and negative, consistent with the well-known asymmetry in volatility responses to return shocks.[24]

The market price of variance risk, $\hat{\xi}_V = -22.38$, is large and significantly negative, reinforcing the idea that investors require substantial compensation to bear variance risk.[25] In

[23] See Bates (2000) and Pan (2002), who estimate similar mean-reversion speeds for stochastic volatility processes using equity and option market data.

[24] A negative correlation between return and variance innovations is consistent with the leverage effect and helps generate negatively skewed return distributions; see Carr and Wu (2009) and Christoffersen et al. (2013).

[25] This finding supports the literature documenting economically significant variance risk premia in equities

contrast, the estimate for the market price of asset-specific risk, $\hat{\xi}_{M\perp V} = 0.24$, is statistically insignificant and estimated with considerable noise. This is consistent with the broader structural credit risk literature, which often finds weak statistical significance for the market price of asset return-specific risk.

The representative firm's idiosyncratic volatility is estimated at $\hat{\sigma}_R = 1.38\%$, which, when combined with leverage, defines the representative firm equity and DH bond volatilities. The estimated coupon is $\hat{c}^R = 0.39$ and contributes to generating economically meaningful leverage.

Moreover, the representative firm's asset Sharpe ratio is approximately 34.98%, broadly consistent with the benchmark calibration in Chen et al. (2009) for investment-grade firms.

As we discuss next, these parameter estimates yield economically meaningful values for key model-implied firm, stock, and bond moment dynamics.

4.4 Dynamics of volatilities, credit spread, and leverage

Panel B of Table 2 evaluates the model's goodness of fit by comparing key empirical variables against their model-implied counterparts over the sample period from January 1997 to December 2022. The table is organized into three panels, each reflecting a different assumption regarding data observability: Panel A reports results for variables assumed to be observed accurately; Panel B presents results for variables observed with measurement error; and Panel C shows the 10-year physical default probability, which was not used in the estimation, and thus entirely out-of-sample.

By construction, the model perfectly matches the averages and standard deviations of the 10-year credit spread and the stock market volatility, as these are the two variables assumed to be observed accurately and directly used for filtering the two state variables. This perfect fit serves as an anchor for the estimation.

Panel B reports on variables that the model estimates under the assumption that their observed values contain measurement errors: the representative firm's total stock volatility, DH corporate bond market volatility, the representative firm's DH corporate bond volatility, and the firm's leverage. The model's implied averages for these variables align closely with their empirical counterparts, suggesting that the model captures the central tendencies well. The model-implied leverage is 43.62%, in line with the mean leverage in the data of 45.06%.[26]

and bonds; see Bollerslev et al. (2009) and Drechsler and Yaron (2011).

[26] The average leverage estimate in our sample is consistent with estimates reported in the broader literature.

In terms of fluctuations, the model replicates the standard deviations reasonably well for most variables, although it tends to underestimate those of the market and representative firm DH corporate bond conditional volatilities.

Importantly, the time-series correlations between the observed variables and their model-implied estimates are high, ranging from 72% for leverage to 86% for the representative firm's DH bond volatility. These strong correlations indicate that the model not only matches the unconditional moments but also captures a significant portion of credit spread and risk dynamics. This finding supports the model's ability to jointly track relevant market- and firm-level risks across both asset classes over time.

Panel C presents the model-implied 10-year physical default probability of 1.50%, which can be compared to the 2.65% historical default rate for BBB-rated firms reported by Standard and Poor's (2022). Although the model estimate is somewhat lower, it remains broadly consistent with the empirical default rate—particularly when considering that the model's default probability is a filtered estimate, conditional on the representative firm for our sample, and computed over a much shorter period than that used for agency default rate estimates.[27]

Figure 3 [about here]

Figure 3 presents the time series of the filtered barrier-to-asset ratio and unlevered asset variance in Panels A and B, respectively. The observables used as inputs for the estimation are shown in the remaining panels. In Panels E to H, we plot the model-implied variables in grey and their empirical counterparts as dashed lines. Panels A and B indicate that the filtered states exhibit reasonable dynamics. Both the barrier-to-asset ratio and the unlevered asset variance display countercyclical behavior, though each follows its own distinct pattern. Turning to the observables measured with error (Panels E–F), we observe that the model-implied time series closely track the empirical data, capturing their key dynamic properties during both periods of market expansion and turmoil.

Overall, the model provides a good in-sample fit to a broad set of observables. It effectively captures key risk dynamics in both stock and bond markets, striking a sound balance between structural rigor and empirical realism.

See Choi et al. (2019), who document average leverage ratios for firms in the CDX universe between 45% and 63% for U.S. large cap in the CDX universe.

[27] See Feldhütter and Schaefer (2018) for a discussion regarding how wide confidence bands around default rates could be.

4.5 Properties of risk premia

The credit risk literature provides numerous insights about the ability of structural credit risk models to capture various aspects of equity and credit market risks. By contrast, there is limited evidence on whether structural credit risk models can generate economically plausible dynamics for expected returns.

We now analyze the model's ability to capture the conditional expected returns in both markets. It is important to emphasize that the model's structural parameters are estimated using the full sample, but without incorporating any information about realized returns beyond their conditional second moments (i.e., volatilities). As a result, analyzing the dynamics and predictive ability of model expected return forecasts constitutes a form of cross-validation–since the model has not been fitted to the realized returns of either market.

We begin by examining the time-series properties of the model's expected return forecasts. The conditional risk premium for the stock and DH bond markets are computed using Proposition 2 based on the estimated parameters and filtered state variables. Figure 4 displays the results: the top panel plots the stock market return forecasts alongside the squared VIX benchmark from Martin (2017), while the bottom panel shows the DH bond market forecasts together with the average 10-year credit spread. We benchmark our model's predictive performance for duration-hedged bond returns using the 10-year credit spread, a choice motivated by two considerations. First, in Merton (1974) framework, credit spreads are closely related to expected excess bond returns, up to default-loss and convexity adjustments. Second, we show that the 10-year credit spread exhibits strong in-sample predictive power and ranks as the third-best predictor in our out-of-sample forecasting horse race.

Figure 4 [about here]

Three key patterns emerge. First, the model forecasts display economically plausible magnitudes and pronounced time variation, with spikes around major market turmoils such as the Dotcom Bubble, the Global Financial Crisis (GFC), and the COVID-19 crisis. Second, the gap between the model forecasts and their respective benchmarks narrows during expansions but widens in periods of heightened uncertainty. Third, the model variables exhibit substantially greater time variation than the benchmarks. Given these preliminary findings, we now turn to a more rigorous analysis of the properties of the model-implied expected returns.

Table 3 reports two sets of predictive regression results. Panel A shows the results obtained by regressing next-month market excess returns measured from month t to $t+1$ on the model-implied conditional expected returns for each market measured as of month t. These forecasts are computed using equation (12) in Proposition 2. For comparison, we benchmark our model using two alternative predictors, the SVIX index for equities and the 10-year credit spread for corporate bonds. We consider three sample periods: the full sample, and the first and second halves. Both monthly returns and predictors are expressed in annualized units, and all regression coefficients are reported on an annual basis. Table 3 presents the results.

Table 3 [about here]

Panel A reports predictive regressions for stock market excess returns. The slope coefficient on the model-implied forecast is close to one and statistically indistinguishable from unity in all samples, while the intercept is small and statistically insignificant throughout. The adjusted R^2 is 1.60% in the full sample and increases to 2.61% in the first subsample, which includes the Global Financial Crisis. Imposing the restriction $\gamma_1^{Model} = 1$ leaves the pricing error insignificant and further reduces its magnitude. In contrast, the SVIX benchmark delivers substantially weaker performance, with an adjusted R^2 of 0.24% in the full sample and a negative slope estimate in the first subsample. Wald tests fail to reject the joint null of a unit slope and zero intercept for the model forecasts in any sample, but reject this null for SVIX in the second half of the sample.

Predictive results for duration-hedged corporate bond returns are stronger. In unrestricted regressions, slope coefficients exceed one and intercepts are negative, but the slopes are not statistically distinguishable from unity. When the restriction $\gamma_1^{Model} = 1$ is imposed, pricing errors decline in absolute value and become statistically insignificant, suggesting that the unrestricted intercepts primarily reflect estimation noise rather than model misspecification. Wald tests do not reject the joint null of a unit slope and zero intercept in any sample. The model exhibits substantial predictive power for bond returns, with adjusted R^2 values between 3.67% and 6.76%, concentrated in the first subsample. Relative to the benchmark predictors, the model produces slope estimates closer to unity and smaller pricing errors across all samples. Although the 10-year credit spread displays meaningful predictability, it underperforms the model except in the second half of the sample, and its explanatory power declines sharply when theoretical restrictions are imposed.

It is well known from Welch and Goyal (2008) that strong in-sample predictive power does not necessarily translate into strong out-of-sample performance. Accordingly, we next examine the model's performance in a more stringent out-of-sample (OOS) setting. The OOS exercise begins with an initial 5-year training window (60 months). Forecasts are generated for the subsequent year, after which the estimation window is expanded by one year, the parameters are re-estimated, and forecasts are again produced for the following year. This procedure is repeated 21 times, yielding an OOS evaluation period from January 2002 to December 2022. Building on the results from Table 3, we use the model-implied expected return, the SVIX, and the 10-year credit spread directly as out-of-sample forecasts, without estimating predictive regressions. Their performance is compared with the full set of Goyal and Welch predictors, whose availability spans 1997-01 to 2022-12, yielding 35 additional predictors for each asset class (38 in total, including the model and the two main benchmarks). For each Goyal–Welch predictor, out-of-sample forecasts are generated from a predictive regression estimated using an analogous expanding-window procedure. Table 4 reports the results.

Table 4 [about here]

Panel A reports out-of-sample R^2_{OS} values computed using a 5-year rolling mean benchmark, whereas Panel B presents results under the zero-mean benchmark. Each panel also reports the p-value associated with the R^2_{OS}, along with the mean, median, and the average R^2_{OS} and p-value for the Goyal and Welch predictors falling above the 75th and 90th percentiles of out-of-sample performance. Tables IA.I and IA.II in the Internet Appendix provide results for all individual predictors.

For equities, the model-implied forecast attains an R^2_{OS} of 2.96% in Panel A and 2.97% in Panel B–performance that is noteworthy given the well-documented difficulty of predicting the equity premium out-of-sample (see Welch and Goyal (2008)). For bonds, where out-of-sample evidence is scarcer, the model delivers R^2_{OS} values of 8.33% and 7.22% across the two panels. For both panels and asset classes, the model's R^2_{OS}s are all statistically significant at the 10% level, and three of the four are significant at the 5% level.

Relative to all other predictors, including the Goyal and Welch variables, the model performs favorably. Its equity premium forecast ranks first in our sample, and the DH bond forecast ranks second. Moreover, both forecasts lie well above the mean and median performance of the top-performing Goyal and Welch predictors in the 75th and 90th percentiles.

Overall, the model provides economically meaningful predictive power across asset classes, sample periods, and in both in-sample and out-of-sample settings. This performance underscores the model's ability to map volatility, leverage, and credit spread dynamics into realistic and useful conditional expected return forecasts.

To better understand which aspects of our approach contribute to our model's predictive performance, we study the forecasting ability of a sequence of alternative asset-pricing frameworks. We consider a reduced-form regression benchmark (Reg.), three simplified credit-model-based specifications (CR1–CR3), and the fully specified structural model (Model). Across all benchmark specifications, expected returns are constructed as the product of stock and bond market exposures and an estimated aggregate asset risk premium. CR1–CR3 share a Merton-based pricing structure in which market exposures depend only on a firm's asset value, i.e., $\beta^A_{M_f}(A^R_t)$. These exposures are obtained from a Merton model estimated to match the same observables as the full structural model, with asset values filtered from the 10-year credit spread. In the regression benchmark, stock and bond exposures are constant and estimated by regressing market excess returns on an aggregate asset factor-mimicking portfolio (FMP) over the full sample. Appendix E details the construction of the FMP. In CR1, the aggregate asset risk premium is constant, whereas in CR2 and CR3 it varies proportionally with a filtered aggregate variance state V_t. We consider two alternative measures of V_t: a return-implied variance filtered from the aggregate asset FMP ("Return"), and a variance path filtered directly from the structural model ("Model"). The return-implied variance is used in Reg. and CR2, while the model-implied variance is used in CR3 and in the full structural model. To summarize, expected return forecasts for Reg. and CR1–CR3 take the form for $f \in \{S, B\}$:

$$\begin{aligned}
\text{Reg.:} \quad \mathbb{E}^{\mathbb{P}}_t\left[R_{M_f,t+1}\right] &= \widehat{\beta}^A_{M_f} \cdot \widehat{\lambda}_A \cdot \widehat{V}_t, && \widehat{V}_t \text{ from FMP,} \\
\text{CR1:} \quad \mathbb{E}^{\mathbb{P}}_t\left[R_{M_f,t+1}\right] &= \widehat{\beta}^A_{M_f}(A^R_t) \cdot \widehat{\lambda}_A, && \\
\text{CR2:} \quad \mathbb{E}^{\mathbb{P}}_t\left[R_{M_f,t+1}\right] &= \widehat{\beta}^A_{M_f}(A^R_t) \cdot \widehat{\lambda}_A \cdot \widehat{V}_t, && \widehat{V}_t \text{ from FMP,} \\
\text{CR3:} \quad \mathbb{E}^{\mathbb{P}}_t\left[R_{M_f,t+1}\right] &= \widehat{\beta}^A_{M_f}(A^R_t) \cdot \widehat{\lambda}_A \cdot \widehat{V}_t, && \widehat{V}_t \text{ from Model.}
\end{aligned} \tag{23}$$

For all specifications except CR1 and the full model, $\widehat{\lambda}_A$ is estimated by forecasting next-month aggregate asset FMP returns using the corresponding lagged variance state over the full sample. For CR1, it is directly obtained from the estimated Merton model.

Table 5 [about here]

Table 5 reports the predictive regression results. Moving from reduced-form and hybrid specifications to the fully specified structural model leads to a systematic improvement in predictive performance for duration-hedged (DH) corporate bond market returns. For stocks, a similar pattern emerges when transitioning from hybrid to fully specified structural frameworks, with the reduced-form regression specification ranking between CR2 and CR3. Comparisons across the Reg., CR1, and CR2 specifications highlight the importance of allowing for time-varying risk premia and conditional market exposures. For both stocks and bonds, comparing the theory-implied R^2 of Reg. and CR1 indicates that introducing conditional risk premia materially enhances return predictability, potentially more so than allowing for conditional exposures alone. Allowing jointly for conditional risk premia and exposures substantially improves bond market predictability, whereas the corresponding evidence for stocks is more mixed. Comparing CR2 and CR3 isolates the role of aggregate variance filtration. Replacing the return-implied variance extracted from aggregate asset factor-mimicking portfolio (FMP) returns with the variance state filtered from the structural model yields stronger and more theory-consistent predictability. This result indicates that the observables used in estimating the structural model contain economically relevant information about aggregate asset uncertainty beyond what is captured by aggregate asset returns alone. Relative to CR3, which combines Merton-based exposures with a model-implied variance state, the fully specified structural model delivers higher adjusted and theory-consistent R^2 values. This improvement reflects the benefits of jointly estimating stock and corporate bond exposures alongside the filtration of firm asset values and aggregate variance, rather than treating exposures and state variables as separate inputs.

4.6 Risk premium decomposition

A key advantage of our dynamic structural model is its ability to decompose expected market returns into their underlying sources of systematic risk. In the model, both systematic asset and variance risks are priced and contribute to the total risk premium in each asset class. We now examine the relative compensation for each of these systematic risk sources across the two markets.

Figure 5 [about here]

Figure 5 plots the conditional asset and variance risk premia for the stock and DH bond markets, $\beta^{A}_{M_f,t} \cdot \lambda_{M,t}$ and $\beta^{V}_{M_f,t} \cdot \lambda_{V,t}$, which are computed using Proposition 2. To discuss the results, it is useful to note that systematic asset risk is procyclical and variance risk is countercyclical. Consequently, the estimated $\hat{\lambda}_{M,t}$ is positive throughout the sample while $\hat{\lambda}_{V,t}$ is negative.

The two top panels show that the equity and DH corporate bonds are both positively exposed to asset risk and derive a positive compensation for this risk. Given that $\hat{\lambda}_{M,t}$ is the same for both markets, the larger asset risk premium for stocks than corporate bonds is due to higher embedded leverage offered by equity (i.e., $\beta^A_{M_S} > \beta^A_{M_B}$). Over our sample, the average conditional asset risk premium for the stock market is about 9.88% while that of DH corporate bond market returns is 2.04%.

A striking implication of our estimated model is that the variance risk premium in corporate bonds is larger in absolute value than in the stock market. Given that the underlying factor risk premium (i.e., $\hat{\lambda}_{V,t}$) is common across markets, the finding arises because the presence of debt tax shields and bankruptcy costs amplifies the negative sensitivity of corporate bond returns to aggregate variance risk relative to equities.

To further assess the relative importance of the two systematic risk components for stocks and corporate bonds, we conduct a three-part complementary analysis. First, we use factor mimicking portfolios (FMPs) to proxy for aggregate asset and variance risk. These proxies correspond to the data counterparts of the model's unlevered risk factors, $dM_t/M_t - rdt$ and $dV_t - \mathbb{E}^{\mathbb{Q}}_t[dV_t]$, respectively. To construct them, we exploit the cross-section of firm-level stocks and corporate bonds in our sample and rely on the firm-level exposure estimates obtained in Section 6. The aggregate asset FMP is formed to have unit exposure to aggregate asset risk and zero exposure to aggregate variance risk, while the aggregate variance FMP is constructed symmetrically. The resulting FMPs earn annualized risk premia of 4.63% ($t = 2.54$) for asset risk and -2.29% ($t = -2.26$) for variance risk. Full construction details are provided in Appendix E.

Using these empirical FMPs, we then examine whether, consistent with Proposition 1, the relative exposures of stocks and bonds to these factors are supported in the data. Panel A of Table 6 reports contemporaneous regressions of stock and DH bond market returns on the two FMPs. Returns are expressed in annualized units, and the coefficients are reported in annual terms.

Table 6 [about here]

A few important insights emerge. First, consistent with the estimated model, both stock and DH bond markets exhibit positive exposure to the asset risk FMP, with stocks displaying greater sensitivity than bonds. Second, the markets' exposures to variance risk differ in both sign and magnitude, with corporate bonds showing larger absolute loadings than equities. Third, the two FMPs explain a greater share of the variation in stock returns than in DH bond returns, suggesting the presence of additional risk sources specific to corporate bonds or incomplete integration between the two markets.[28]

Having established the contemporaneous factor structure of both markets, we turn to the predictive dimension to evaluate how each risk premium component help forecasts future returns. Proposition 2 states that total conditional risk premia decompose into asset and variance components. Using the full-sample exposures reported in Panel A and the empirical (as opposed to model-filtered) FMP realizations, we construct hedged returns against either asset or variance risk. For each market $f \in \{S, B\}$ (stocks or DH bonds), hedged returns are computed as $R_{M_f,t} - \beta^F_{M_f} F_t$, where $R_{M_f,t}$ denotes the market excess (or duration-hedged) return, $\beta^F_{M_f}$ is the corresponding factor exposure, and F_t is the realization of the FMP proxies of asset or variance risk on month t. By construction, these hedged returns isolate the contribution of the remaining risk factor to realized returns. For instance, stock market returns hedged against variance (asset) risk should, in theory, primarily reflect exposure to asset (variance) risk. The same logic applies to DH bond returns, which are already hedged for interest rate risk and are further adjusted to isolate either asset or variance risk exposure. We then regress next month hedged returns of either market measured from month t to $t+1$ on month-t $\beta^A_{M_f,t}\lambda_{A,t}$ for variance risk hedged returns or $\beta^V_{M_f,t}\lambda_{V,t}$ when hedging returns against asset risk. Panel B of Table 6 reports the results.

The table reveals several meaningful insights. First, the model-based asset and variance risk premium predictors consistently exhibit positive loadings, supporting the idea that these components are positively related to next-month hedged market returns. The estimated slopes are statistically indistinguishable from unity while the intercepts are generally insignificant, except in one case for variance and duration hedged bond returns.

Comparing the regression's adjusted R^2 reported in the first with the second column of Panel B, we conclude that the predictability of stock market returns is almost entirely attributable to aggregate asset risk. Similar to the stock market case, the asset risk premium component for bonds, $\beta^A_{M_B,t}\lambda_{A,t}$, contains significant predictive information. However, in con-

[28]See, for example, Collin-Dufresne et al. (2024) and Sandulescu (2020) for discussions of integration between equity and corporate bond markets.

trast to stocks, the variance risk premium for bonds explains a non-trivial share of return variation. Taken together, these results corroborate the view that variance risk plays a more prominent role in pricing corporate bonds than equities.

While the potential presence of priced factors in one market but not the other is of independent interest, it does not diminish the economic relevance of a unified framework. If anything, the results reported so far illustrate that joint models of equity and credit markets provide a powerful framework to capture common valuation drivers and to quantify how certain systematic sources of risks jointly shape stock and corporate bond return dynamics.

5 Equity and Credit Industry Analysis

We now assess model performance across the twelve Fama–French industry groups. We begin by presenting summary statistics and estimating the structural parameters governing the dynamics of the representative firm in each industry. We then evaluate the model's fit for key industry-level characteristics: volatility, credit spreads, and leverage. Finally, we examine conditional risk premia, assess their predictive power, and analyze the respective roles of asset and variance risk premia across industry portfolios.

5.1 Summary statistics, estimation, and parameter estimates

Our industry-level analysis begins by examining key variables of interest. Table IA.III in the Internet Appendix reports descriptive statistics for industry portfolio stock and corporate bond returns, representative-firm stock and bond volatilities, credit spreads, leverage, and total debt. The construction of these variables is detailed in Section 3.2. The twelve industries exhibit substantial cross-sectional variation. Mean excess stock returns range from 11.23% for Business Equipment to 2.29% for Consumer Durables, while DH bond portfolio returns range from 2.48% for Energy and Telecom to −0.05% for Consumer Durables. Finance and Consumer Durables are the most highly levered sectors in terms of total debt, whereas Chemicals exhibits the lowest debt levels. Average 10-year credit spreads range from 128.51 bps for Chemicals to 291.33 bps for Consumer Durables. Industry-level leverage varies substantially, from 0.28 for Health Care to 0.68 for Finance.

To further illustrate the heterogeneity in industry risk dynamics, Figure 6 plots the time series of the risk variables used to estimate each industry's representative firm dynamics. These include stock and DH bond return volatility, credit spreads, and leverage. Each row presents a specific variable, while each column corresponds to a subset of four industries. The figure highlights pronounced and persistent differences in risk dynamics across industries, underscoring the need for industry-specific parameterization.

Figure 6 [about here]

For consistency, industry-level estimation takes as given the dynamics of systematic risks, $\{\hat{\kappa}, \hat{\theta}, \hat{\delta}, \hat{\rho}, \hat{\xi}_{M\perp V}, \hat{\xi}_V\}$ and $\{\hat{V}_t\}_{t\geq 0}$, obtained from the market-level estimation. The default barrier A_D^R is fixed at two-thirds of the industry-average debt level (in \$ billions), leaving three parameters to estimate for each industry I's representative firm: $\Theta_I \equiv \{\beta_R, \sigma_R, c^R\}$.[29] Each month, $\hat{A}_t^R$ is recovered by solving $CS_{10,t}^I = CS_{10}(\hat{A}_t^R, \hat{V}t; \Theta)$, where $CS_{10,t}^I$ denotes the industry-level credit spread. The likelihood treats credit spreads as observed and assumes Gaussian relative pricing errors for representative-firm stock volatility, bond volatility, and leverage. Full details are provided in the Internet Appendix IA.2.

Table IA.IV in the Internet Appendix presents the parameter estimates. Unlevered asset betas range from 0.68 for Utilities to 1.35 for Energy. Utilities exhibit the lowest asset idiosyncratic volatility, whereas Health Care has the highest at 3.71%. These pronounced cross-sectional differences in the estimated parameters are not surprising and are necessary for the model to capture the substantial disparities in risk dynamics observed empirically.

In light of this heterogeneity, the model's ability to account for the risk and return of both stocks and corporate bonds across industries would be particularly noteworthy.

5.2 Dynamics of volatilities, credit spread, and leverage

Table 7 evaluates the model's goodness of fit by comparing empirical quantities to their model-implied counterparts. We do not report results for the 10-year credit spread, as this variable is perfectly fitted when filtering the representative firm's unlevered asset values for each industry. The model closely matches average stock volatility, bond volatility, and leverage across industries. Time-series correlations between observed and model-implied variables are high on average—68% for stock volatility, 79% for bond volatility, and 54% for leverage. Given that firm dynamics are governed by only three industry-specific parameters and a single state variable

[29] Recall that, for simplicity, we do not distinguish between market- and industry-level parameters or asset values of the representative firms in the notation.

once systematic risks are conditioned upon, the model's ability to capture both the level and heterogeneity of industry risk dynamics is noteworthy.

Table 7 [about here]

Our previous analysis of market portfolio returns highlights the strong predictive content of the model's conditional risk premium forecasts for both stocks and DH bonds. We now examine whether these results extend to industry portfolios.

5.3 Properties of risk premia

Using the industry-level estimated structural parameters and the filtered state variable, we apply the result in Proposition 2 to construct forecasts of expected excess returns for stocks and DH bond returns for industry portfolios. It should be noted that our homogeneity assumption implies that the exposure of the representative firm stock or DH bond to a given source of systematic risk is equal to that of a portfolio made of these securities. This, without requiring idiosyncratic risk to diversify away in industry portfolios (see Appendix C for the details).

Tables 8 and IA.V report two sets of predictive regression results—Table 8 for our model and Table IA.V for the benchmarks. In each table, Panel A presents the results from regressions of next-month excess for stocks and Panel B for DH bonds returns. We use the model-implied conditional expected returns for each industry as predictor in Table 8. For comparison, we benchmark our model against the squared VIX index for equities and against the industry-level 10-year credit spread for corporate bonds in Table IA.V. All coefficient estimates are annualized.

Tables 8 [about here]

For industry stock portfolios, the model exhibits economically meaningful predictive power. Portfolio intercepts, γ_0^{Model}, vary in sign but are uniformly small and statistically insignificant. In contrast, the slope coefficients on model-implied expected returns, γ_1^{Model}, are statistically significant at the 10% level for 8 of the 12 industries and cluster tightly around unity. The adjusted R^2 reaches 3.04% for Chemicals and exceeds 1% for seven industries, indicating that the model captures economically relevant time variation in conditional risk premia beyond standard benchmarks. With the exception of three industries, the theory-imposed adjusted R^2 exceeds its unrestricted counterpart, suggesting that the model's structural restrictions improve explanatory power rather than constrain it. Pricing errors are small in magnitude, fluctuate in sign, and are statistically insignificant for all but one industry, Consumer Durables.

Predictability is substantially stronger for duration-hedged corporate bond returns. The slope coefficients on model-implied expected returns are statistically significant at conventional levels for nearly all industries, pointing to pervasive and economically meaningful predictability in credit markets. The model explains a nontrivial share of return variation, with both adjusted and theory-constrained R^2 values typically in the 4–5% range. On average across industries, annualized pricing errors are small and never statistically significant, indicating that the model prices cross-industry variation in bond returns without systematic bias.

Relative to the benchmark regressions reported in Table IA.V, the model delivers systematically stronger and more robust predictive performance across both asset classes and industries. By contrast, the benchmark slope coefficients are rarely statistically significant at conventional while explanatory power is modest and unstable. These results indicate that the gains in predictive performance stem not from mechanical fitting but from the model's ability to extract economically relevant time variation in expected returns that is largely absent from reduced-form benchmark regressions.

5.4 Risk premium decomposition

Next, we investigate the decomposition of risk premia across industries, which is informative for two reasons. First, the finding that the variance risk premium is larger in absolute value for duration-hedged corporate bonds than for equities at the aggregate market level warrants further scrutiny to assess whether this pattern persists across industries. Second, existing evidence on the relative pricing of asset and variance risk in equity and corporate bond markets is limited, and, to our knowledge, there is no prior evidence on the cross-sectional distribution of these premia across industries and asset classes. An industry-level analysis therefore provides a novel perspective on how asset and variance risks are priced within and across equity and credit markets.

Table 9 [about here]

Table 9 reports industry-level averages of total conditional risk premia and their decomposition into asset and variance risk components. Panel A presents results for equity portfolios, and Panel B for duration-hedged (DH) corporate bonds. Consistent with earlier findings, total conditional risk premia exhibit substantial cross-sectional heterogeneity across industries in both asset classes. The asset risk premium is uniformly larger for stocks than for DH bonds, in line with economic intuition and the model's implications.

In contrast, variance risk premia display a markedly different pattern. For equities, the variance risk premium is small on average but economically meaningful in several industries, notably Finance, Energy, and Consumer Durables. Comparing Panels A and B reveals that the variance risk premium for DH bonds is larger in absolute value than for stocks in every industry, underscoring the heightened exposure of credit markets to aggregate variance risk.

To illustrate the time-series dynamics underlying these averages, Figures IA.1 and IA.2 plot model-implied conditional risk premia for industry stock portfolios and DH bonds, respectively. These figures reveal pronounced variation in risk premia across asset classes, industries, and over time. In particular, Figure IA.1 shows that equity variance risk premia spike during periods of market stress in certain industries while remaining muted in others, a pattern mirrored in the DH bond market.

Because the prices of systematic asset and variance risk, $\hat{\lambda}_{A,t}$ and $\hat{\lambda}_{V,t}$, are common across asset classes and industries, these patterns arise from heterogeneous exposures rather than differences in risk prices. This highlights the model's ability to generate economically meaningful cross-sectional and time-series variation in expected returns through endogenous differences in risk exposure.

6 Equity and credit firm-level analysis

The credit risk literature has evolved along two distinct but complementary paths. One strand relies on market-wide representative firm models to characterize the joint dynamics of equity and credit markets in a tractable framework (Collin-Dufresne et al., 2024; Doshi et al., 2024, among others). While these models are somewhat more practical empirically, they abstract from the rich cross-sectional heterogeneity that characterizes real financial markets. A second strand of research places greater emphasis on capturing cross-sectional differences across firms, recognizing that firms in distinct industries may have different levels of unlevered asset risk, financial leverage, and sensitivities to systematic sources of risk (see Bhamra et al., 2010b,a). Our final analysis bridges these two approaches by extending the representative firm framework to the firm level and estimating asset value dynamics for the full cross-section of firms. This extension allows us to examine how well the model captures cross-sectional differences in risk exposures and expected returns, and to evaluate its predictive performance relative to benchmark specifications and alternative factor-based frameworks.

6.1 Filtering firm asset values

To obtain firm-level return forecasts, we first filter firm asset values. For consistency with the market-level analysis, we take the systematic risk parameters $\{\hat{\kappa}, \hat{\theta}, \hat{\delta}, \hat{\rho}, \hat{\xi}_{M\perp V}, \hat{\xi}_V\}$ and $\{\hat{V}_t\}_{t\geq 0}$, directly from the market-level estimation. For each firm j, we assign asset beta β_j and idiosyncratic volatility σ_j equal to the representative-firm estimates $\hat{\beta}_R$ and $\hat{\sigma}_R$ of its industry, as reported in Table IA.IV. We set the default barrier A_D^j to two-thirds of the firm's average total debt (in \$ billions) and calibrate the coupon c^j proportionally as $c^j = A_D^j \times (\hat{c}^R / A_D^R)$, using the industry representative firm's coupon-to-barrier ratio.

Given these inputs, we back out firm-level asset values $\hat{A}_t^j$ from observed 10-year credit spreads. This procedure delivers a tractable approximation to the asset value dynamics that would arise from a full structural estimation at the firm level. Such a full-fledged estimation is infeasible in practice due to data limitations, in particular the short and incomplete time series of corporate bond returns available for many firms.

6.2 In the cross-section of firm exposures and expected returns

To assess the relevance of model-implied exposures in the cross-section, we require empirical factor proxies that allow us to estimate unconditional stock and duration-hedged (DH) corporate bond exposures directly from the data. These data-driven exposures provide a benchmark against which the model-implied exposures can be evaluated. A close correspondence between the two would offer strong evidence in favor of the model's identification strategy and its underlying pricing mechanism, demonstrating that the structural restrictions embedded in the model successfully recover economically meaningful patterns in observed returns.

Using firm-level stock and corporate bond exposures, we construct empirical factor-mimicking portfolios (FMPs) for aggregate asset and variance risk. These portfolios replicate the model's unlevered risk factors by construction, delivering unit exposure to the target factor and zero exposure to the other. Appendix E provides full details on the construction and validation of these portfolios. We use these empirical factors to characterize the factor structure of equity and credit markets and to decompose return predictability in Table 6.

To assess the economic relevance of the firm-level exposures and the relative contribution of asset and variance risk in stock and duration-hedged (DH) corporate bond returns, we focus on elasticities, defined as the percentage change in portfolio returns associated with a one–standard deviation increase in a given factor. Each month, firms are independently sorted into quintile portfolios based on four measures of default risk: market leverage, the model-implied barrier-to-asset ratio, the 10-year credit spread, and a composite index constructed as the average of the three z-scored characteristics. Within each portfolio, stock and DH bond returns are computed using equal weights.

Empirical elasticities are obtained by estimating full-sample time-series regressions of portfolio returns on the aggregate asset and variance FMPs and scaling the estimated factor loadings by the corresponding factor volatilities. Model-implied elasticities are constructed by averaging firm-level model-implied exposures within each portfolio each month and scaling these averages by the volatility of the corresponding FMP. This approach delivers a direct and economically interpretable comparison between purely data-driven and model-implied sensitivities across the default-risk dimension.

Figure 7 [about here]

Across all conditioning variables, empirical and model-implied elasticities for both stocks and duration-hedged (DH) corporate bonds display a close correspondence. Asset-risk elasticities are nearly identical across the two approaches, consistent with the evidence in Schaefer and Strebulaev (2008). For variance risk, the elasticities are of comparable magnitude, although some dispersion across portfolios remains. Importantly, the empirical elasticities exhibit the correct signs and broadly mirror the patterns implied by the model, increasing in absolute value for both stocks and duration-hedged corporate bonds as default risk rises. Taken together, these findings support the model's ability to generate empirically realistic cross-sectional patterns in factor exposures at the firm level.

We next examine the model's ability to account for the cross-section of expected returns on stock, DH bond, and balanced portfolios (60% stock, 40% DH bond). Each month, firms are independently sorted into ten portfolios based on size, book-to-market, CAPM-style regression-based stock and DH bond market betas, and leverage. Portfolio excess (or DH) returns are computed using equal weights, and we summarize performance using the time-series average return of each portfolio. For comparison, we construct portfolio-level model forecasts by averaging the firm-level expected returns within each portfolio each month and then taking the time-series mean. Figure 8 reports the resulting average realized returns, their model-implied counterparts, and the regression fit—slope and adjusted R^2—from cross-sectional regressions of average returns on the model forecasts.

Figure 8 [about here]

Across all conditioning variables and asset classes, the slope of the cross-sectional regression of realized returns on model-implied expected returns is uniformly positive, indicating a systematic alignment between characteristic-sorted return differences and the model's implied expected returns. The associated explanatory power is economically large. For equities, the average cross-sectional adjusted R^2 is 44%, with values reaching as high as 91% for size-sorted portfolios. For duration-hedged corporate bonds, explanatory power is even stronger on average, with a mean adjusted R^2 of 64%. The model also performs well for a balanced 60/40 equity–bond allocation, where the average cross-sectional R^2 is 57% and reaches nearly 90% for size-based sorts.

Performance varies across conditioning variables, but remains consistently strong. Size-sorted portfolios exhibit particularly high explanatory power across all asset classes, while book-to-market sorts display more modest but still meaningful fit, especially for equities and the balanced portfolio. Overall, the figure shows that the model captures a substantial fraction of cross-sectional return dispersion across firm characteristics, delivering both correct pricing direction and economically significant explanatory power.

6.3 Testing the model at the firm level

Our final test evaluates the performance of model-implied expected return forecasts at the firm level for both stocks and duration-hedged corporate bonds. To assess the economic relevance of these firm-level forecasts, we compare them to benchmark expected returns obtained from observable conditional factor models that have been shown to jointly explain equity and corporate bond returns, as well as from latent factor models estimated using Instrumented Principal Components Analysis (IPCA) (Kelly et al., 2020).

Let $R_{f,j,t+1}$ denote the excess or duration-hedged return on firm j between t and $t+1$, where $f = S$ refers to stock returns in excess of the one-month Treasury bill rate and $f = B$ refers to duration-hedged excess returns on corporate bonds. For each firm j, time t, and contingent claim f, we denote by $\lambda^k_{f,j,t}$ the conditional risk premium implied by model/specification k.

To test each model, we follow Martin and Wagner (2019) and estimate the pooled panel regression for a given asset class f,

$$R_{f,j,t+1} = \gamma^k_0 + \gamma^k_1 \lambda^k_{f,j,t} + \varepsilon^k_{j,t+1}, \tag{24}$$

where $\varepsilon^k_{j,t+1}$ is an error term. We report t-statistics computed from robust standard errors that are clustered by both firm and month to account for cross-sectional and time-series dependence in the residuals. A correctly specified model k that delivers conditionally unbiased forecasts should satisfy $\gamma^k_0 = 0$ and $\gamma^k_1 = 1$. We benchmark our model against a set of latent and observable conditional factor models that are estimated separately for each market. Because the extracted factors are asset-class specific, this approach provides a particularly favorable setting for the IPCA models. We consider five IPCA models with $n_F \in \{2, 3, 5, 10\}$ latent factors. For both markets, the factors are instrumented with the Kelly et al. (2023)'s 29 stock and bond characteristics and a constant. The IPCA conditional expected excess return forecasts are given by $\lambda^{\text{IPCA}}_{f,j,t+1} = z'_{i,t}(\widehat{\Gamma}_{\alpha,f} + \widehat{\Gamma}_{\beta,f}\,\widehat{\mu}_f)$, where $z_{j,t}$ collects the firm characteristics, $\widehat{\Gamma}_{\alpha,f}$ and $\widehat{\Gamma}_{\beta,f}$ are the subset of IPCA loading matrices, and $\widehat{\mu}_f$ denotes the time-series averages of the traded factor realizations (their risk premia) estimated for asset class f.

As observable factor benchmarks, we consider the He et al. (2017) two-factor intermediary capital model (HKM), which includes the stock market factor and the traded intermediary capital factor, and the original Fama and French (1993) five-factor model (FF5), which includes the Fama-French three factors together with the default spread (DEF) and term spread ($TERM$) corporate bond factors. We estimate conditional versions of these factor models where we instrument the firm exposures with the same set of characteristics we use in IPCA (Kelly et al., 2019).[30] We also estimate a two-factor model designed to capture liquidity risk using the traded stock and corporate bond liquidity factors of Pastor and Stambaugh (2003) over the shorter sample 2003:08–2022:12, since construction of the corporate bond liquidity factor requires the availability of TRACE transaction data.[31] To interpret the results presented next, it is impor-

[30] We fully describe the IPCA methodology for both latent and pre-specified factors in Section IA.4 of the Internet Appendix.

[31] To construct the traded Pastor and Stambaugh (2003) liquidity factor for corporate bonds, we follow

tant to note that, unlike the benchmark frameworks, which are estimated separately for each market, the structural model is estimated jointly across markets and is not fitted directly to realized returns. Table 10 reports the results.

Table 10 [about here]

First, the Wald test of the joint hypothesis $\gamma_0 = 0$ and $\gamma_1 = 1$ for both stocks and bonds is not rejected at the 1% and 5% levels across all models, although it is marginally rejected for bonds in our model and in the two-factor IPCA framework. Across all models, the intercept γ_0 is not statistically different from zero for stocks. For corporate bonds, however, the intercept is statistically significant for the structural model but not for the benchmark specifications. This result echoes our earlier findings for the market- and industry-level analyses and is mechanically driven by an estimated slope coefficient exceeding one. For both stocks and corporate bonds, the γ_1 coefficients are not statistically different from one, while being statistically significant relative to zero. Overall, these results suggest that all models provide a reasonable characterization of expected returns for stocks and duration-hedged (DH) corporate bonds at the firm level. In terms of explanatory power, all models are broadly consistent with their theoretical mapping, as reflected by the close alignment between their adjusted and theory-implied R^2 values. To complement these measures, we also consider the predictive R^2, which captures how well cross-sectional differences in average returns are explained by the model-implied conditional expected returns. In other words, $R^2_{Pred.}$ reflects a given model's ability to describe risk across firms rather than by common time-series variation alone (Kelly et al., 2019; Büchner and Kelly, 2022). While firm-level stock return predictability is inherently weaker than for corporate bonds, the structural model nonetheless dominates all benchmark specifications for equities. This result holds across all R^2 measures considered as indicated in Panel A. Specifically, $R^2_{Adj.}$ equals 0.69% for our model, compared to 0.14–0.13% for HKM and FF5, and at most 0.06% for the IPCA models. In terms of $R^2_{Pred.}$, the structural model explains 1.48% of next-month stock excess returns, compared to 0.94% for HKM, the second-best performing model. Relative to the benchmark frameworks, Panel B shows that the model also delivers the highest predictive power for duration-hedged corporate bonds. Across R^2 measures, the model's predictive power ranges from 2.31% to 2.85%, comparing favorably to HKM, which delivers R^2 values between 0.60% and 1.09%. Comparing the results in Panels A and B, the

Lin et al. (2011).

model exhibits similar magnitudes for adjusted, theory-implied, and predictive R^2 measures, in contrast to the benchmark frameworks for which cross-sectional fit is much higher (i.e., $R^2_{Pred.}$ is systematically higher than $R^2_{Adj.}$ or R^2_{Theory}). Taken together, these results indicate that the model provides a coherent characterization of both time-series and cross-sectional variation in firm-level stock and duration-hedged corporate bond returns.

In the Internet Appendix, Table IA.VI reproduces the results over a shorter sample spanning 2003:08–2022:12 covering two liquidity factors (LIQ) comprising Pastor and Stambaugh (2003)'s stock and corporate bond traded liquidity factors, which relies on TRACE data. Results are broadly consistent, with our model delivering consistently stronger explanatory performance than liquidity-based models, intermediary capital asset-pricing frameworks, and latent factor models.

Finally, the favorable performance of the model relative to the benchmarks suggests that the model's aggregate asset variance, filtered within the structural framework, captures economically relevant information about uncertainty that is not already spanned by liquidity or intermediary capital factors.

7 Conclusion

We study the joint dynamics of risk and return in equity and credit markets by implementing a structural model drawn from recent advances in the credit risk literature. Applying the model at the market, industry, and firm levels, we assess its empirical performance in capturing the risk and expected return of various segments of stock and corporate bond markets.

The model yields several important and novel insights. First, if one accepts the existence of an unconditional one-factor structure for unlevered asset values—where factor volatility is time-varying—then both stocks and duration-hedged corporate bonds should follow a conditional two-factor structure governed by priced exposures to unlevered aggregate asset and variance risks. We rigorously estimate this structure at both aggregate and disaggregated levels to evaluate its ability to capture the dynamics of risk and expected returns.

Our empirical findings are striking. Despite its parsimonious nature, the model provides an excellent fit for both asset classes. In-sample, it successfully replicates the observed dynamics of stock and bond volatility, credit spreads, and firm leverage—at the market, industry, and firm levels. Crucially, the model's conditional expected return forecasts contain economically meaningful information: the risk premia are statistically significant, of plausible magnitudes, and highly predictive of future realized returns across both stocks and corporate bonds, and across all levels of aggregation. Among other things, we show that the model characterizes well the time series of market and industry portfolios, as well as both the time-series and cross-sectional variation in firm-level returns. Analyzing its performance against various benchmarks, we further demonstrate that the model delivers superior empirical performance.

While the pricing of variance risk has received substantial attention in the equity literature, it has been largely overlooked in the context of corporate bond returns. We demonstrate that variance risk commands a significantly larger premium in corporate bonds than in equities. Moreover, this component of risk compensation is a key driver of return predictability in credit markets, while remaining relatively muted in equity markets.

Our contribution is not purely theoretical in nature, nor do we propose new factors for the "zoo" to explain the joint cross-section of stocks and bonds. Rather, we show that a well-specified and rigorously estimated structural credit risk model provides a powerful, unified framework for studying the joint dynamics of risk and return across asset classes. This highlights the value of credit risk models as consistent, empirically grounded tools for understanding the pricing of systematic risk in equity and credit markets.

References

Adrian, T., E. Etula, and T. Muir (2014). Financial intermediaries and the cross-section of asset returns. *Journal of Finance 69*(6), 2557–2596.

Aït-Sahalia, Y. and R. L. Kimmel (2010). Estimating affine multifactor term structure models using the likelihood function. *Journal of Financial Economics 98*(1), 113–144.

Andreani, M., D. Palhares, and S. Richardson (2024). Computing corporate bond returns: a word (or two) of caution. *Review of Accounting Studies 29*(4), 3887–3906.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance 61*(1), 259–299.

Bansal, R. and A. Yaron (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance 59*(4), 1481–1509.

Bates, D. S. (2000). Post-'87 crash fears in the s&p 500 futures option market. *Journal of Econometrics 94*(1-2), 181–238.

Berger, D., I. Dew-Becker, and S. Giglio (2020). Uncertainty shocks as second-moment news shocks. *The Review of Economic Studies 87*(1), 40–76.

Bhamra, H. S., L.-A. Kuehn, and I. A. Strebulaev (2010a). The aggregate dynamics of capital structure and macroeconomic risk. *Review of Financial Studies 23*(12), 4187–4241.

Bhamra, H. S., L.-A. Kuehn, and I. A. Strebulaev (2010b). The levered equity risk premium and credit spreads: A unified framework. *Review of Financial Studies 23*(2), 645–703.

Bollerslev, T., G. Tauchen, and H. Zhou (2009). Expected stock returns and variance risk premia. *Review of Financial Studies 22*(11), 4463–4492.

Brennan, M. J. and E. S. Schwartz (1978). Corporate income taxes, valuation, and the problem of optimal capital structure. *Journal of Business 51*(1), 103–114.

Büchner, M. and B. Kelly (2022). A factor model for option returns. *Journal of Financial Economics 143*(3), 1140–1161.

Campbell, J. Y., J. Hilscher, and J. Szilagyi (2008). In search of distress risk. *Journal of Finance 63*(6), 2899–2939.

Campbell, J. Y. and G. B. Taksler (2003). Equity volatility and corporate bond yields. *The Journal of finance 58*(6), 2321–2350.

Campello, M., L. Chen, and L. Zhang (2008). Expected returns, yield spreads, and asset pricing tests. *The Review of Financial Studies 21*(3), 1297–1338.

Carr, P. and L. Wu (2009). Variance risk premiums. *Review of Financial Studies 22*(3), 1311–1341.

Chen, H. (2010). Macroeconomic conditions and the puzzles of credit spreads and capital structure. *The Journal of Finance 65*(6), 2171–2212.

Chen, H., P. Collin-Dufresne, and R. S. Goldstein (2009). On the relation between the credit spread puzzle and the equity premium puzzle. *Review of Financial Studies 22*(9), 3367–3409.

Chen, Z., N. L. Roussanov, X. Wang, and D. Zou (2024). Common risk factors in the returns on stocks, bonds (and options). Technical report, Working paper.

Choi, J. (2013). What drives the value premium?: The role of asset risk and leverage. *The Review of Financial Studies 26*(11), 2845–2875.

Choi, J., D. Hackbarth, and E. Mendoza (2019). Leverage dynamics over the business cycle. *Review of Financial Studies 32*(6), 2152–2198.

Choi, J. and Y. Kim (2018). Anomalies and market (dis)integration. *Journal of Monetary Economics 100*, 16–34.

Choi, J. and M. Richardson (2016). The volatility of a firm's assets and the leverage effect. *Journal of Financial Economics 121*(2), 254–277.

Christoffersen, P., S. Heston, and K. Jacobs (2013). Skewness, skewness premia and the predictability of equity returns. *Review of Financial Studies 26*(5), 1407–1448.

Clark, T. E. and K. D. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics 138*(1), 291–311.

Collin-Dufresne, P., B. Junge, and A. B. Trolle (2024). How integrated are credit and equity markets? evidence from index options. *The Journal of Finance 79*(2), 949–992.

Culp, C. L., Y. Nozawa, and P. Veronesi (2018, February). Option-based credit spreads. *American Economic Review 108*(2), 454–488.

Davydenko, S. (2012). When Do Firms Default? A Study of the Default Boundary. Working Paper, University of Toronto.

Dickerson, A., M. Fournier, A. Jeanneret, and P. Mueller (2023). A credit risk explanation of the correlation between corporate bonds and stocks. *Working Paper*.

Dickerson, A., P. Mueller, and C. Robotti (2023). Priced risk in corporate bonds. *Journal of Financial Economics 150*(2), 103707.

Doshi, H., J. Ericsson, M. Fournier, and S. Byung Seo (2024). The risk and return of equity and credit index options. *Journal of Financial Economics 161*.

Doshi, H., K. Jacobs, P. Kumar, and R. Rabinovitch (2019). Leverage and the cross-section of equity returns. *The Journal of Finance 74*(3), 1431–1471.

Drechsler, I. and A. Yaron (2011). What's vol got to do with it. *Review of Financial Studies 24*(1), 1–45.

Du, D., R. Elkamhi, and J. Ericsson (2019). Time-varying asset volatility and the credit spread puzzle. *The Journal of Finance 74*(4), 1841–1885.

Duffie, D. and K. J. Singleton (2003). *Credit Risk: Pricing, Measurement, and Management.* Princeton University Press.

Eraker, B. and Y. Wu (2017). Explaining the negative returns to volatility claims: An equilibrium approach. *Journal of Financial Economics 125*(1), 72–98.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Feldhütter, P. and S. M. Schaefer (2018). The myth of the credit spread puzzle. *The Review of Financial Studies 31*(8), 2897–2942.

Friewald, N., C. Wagner, and J. Zechner (2014). The cross-section of credit risk premia and equity returns. *Journal of Finance 69*(6), 2419–2469.

Goyal, A., I. Welch, and A. Zafirov (2024). A comprehensive 2022 look at the empirical performance of equity premium prediction. *The Review of Financial Studies 37*(11), 3490–3557.

He, Z., B. Kelly, and A. Manela (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics 126*(1), 1–35.

Huang, J.-Z. and Z. Shi (2021). What do we know about corporate bond returns. *Annual Review of Financial Economics* (13), 363–399.

Kelly, B., D. Palhares, and S. Pruitt (2023). Modeling corporate bond returns. *Journal of Finance 78*(4), 1967–2008.

Kelly, B. T., S. Pruitt, and Y. Su (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics 134*(3), 501–524.

Kelly, B. T., S. Pruitt, and Y. Su (2020). Instrumented principal component analysis. *Working Paper*.

Kung, H. and L. Schmid (2015). Innovation, growth, and asset prices. *Journal of Finance 70*(3), 1001–1037.

Leland, H. E. (1994). Corporate debt value, bond covenants, and optimal capital structure. *The Journal of Finance 49*(4), 1213–1252.

Lin, H., J. Wang, and C. Wu (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics 99*(3), 628–650.

Martin, I. (2017). What is the expected return on the market? *The Quarterly Journal of Economics 132*(1), 367–433.

Martin, I. W. and C. Wagner (2019). What is the expected return on a stock? *The Journal of Finance 74*(4), 1887–1929.

McQuade, T. (2018). Stochastic volatility and asset pricing puzzles. *Available at SSRN 3222902*.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica 41*(5), 867–887.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance 29*(2), 449–470.

Pan, J. (2002). The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics 63*(1), 3–50.

Pastor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*(3), 642–685.

Saita, L. (2005). The puzzling price of corporate default risk. *Working paper*.

Sandulescu, M. (2020). How integrated are corporate bond and stock markets? Technical report, Swiss Finance Institute.

Schaefer, S. M. and I. A. Strebulaev (2008). Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds. *Journal of Financial Economics 90*(1), 1–19.

Todorov, V. (2010). Variance risk-premium dynamics: The role of jumps. *The Review of Financial Studies 23*(1), 345–383.

van Binsbergen, J. H., Y. Nozawa, and M. Schwert (2025, January). Duration-based valuation of corporate bonds. *Review of Financial Studies 38*(1), 158–191.

Vasicek, O. (2002). Probability of loss on a loan portfolio. *Risk*, 160–162.

Vassalou, M. and Y. Xing (2004). Default risk in equity returns. *The Journal of Finance 59*(2), 831–868.

Welch, I. and A. Goyal (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies 21*, 1455–1508.

Appendix

A Risk-neutralization and factor risk premia

According to Girsanov's theorem, this SDF implies the following dynamics of M_t and V_t under the risk-neutral measure $\mathbb{Q}$:

$$\frac{dM_t}{M_t} = rdt + \sqrt{V_t}dW_t^{M,\mathbb{Q}}, \tag{A.25}$$

$$dV_t = \kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}} - V_t)dt + \delta\sqrt{V_t}dW_t^{V,\mathbb{Q}}, \tag{A.26}$$

where $dW_t^{M,\mathbb{Q}} = \rho dW_t^{V,\mathbb{Q}} + \sqrt{1-\rho^2}dW_t^{M\perp V,\mathbb{Q}}$, $\kappa^{\mathbb{Q}} = \kappa + \delta\xi_V$, and $\theta^{\mathbb{Q}} = \kappa\theta/\kappa^{\mathbb{Q}}$.[32]

Given equations (??) and (A.25), the unlevered market risk premium defined as $\mathbb{E}_t^{\mathbb{P}}\left[\frac{dM_t}{M_t}\right] - \mathbb{E}_t^{\mathbb{Q}}\left[\frac{dM_t}{M_t}\right]$ is given by

$$\mathbb{E}_t^{\mathbb{P}}\left[\frac{dM_t}{M_t}\right] - \mathbb{E}_t^{\mathbb{Q}}\left[\frac{dM_t}{M_t}\right] = (\mu_t - r)\,dt = \left(\sqrt{1-\rho^2}\xi_{M\perp V} + \rho\xi_V\right)\cdot V_t dt. \tag{A.27}$$

Moreover, equations (3) and (A.26) implies that the unlevered asset variance risk premium, $\mathbb{E}_t^{\mathbb{P}}[dV_t] - \mathbb{E}_t^{\mathbb{Q}}[dV_t]$, is

$$\mathbb{E}_t^{\mathbb{P}}[dV_t] - \mathbb{E}_t^{\mathbb{Q}}[dV_t] = (\xi_V\delta)\cdot V_t dt, \tag{A.28}$$

where we have used the fact that $\theta^{\mathbb{Q}}\cdot\kappa^{\mathbb{Q}} = \kappa\cdot\theta$.

B Contingent claim pricing

Prices of a firm's securities and contingent claims depend on the risk-neutral distribution of τ_j and are a function of two key quantities: (i) the present value of a dollar received at default $P_D(A_t^R, V_t) = \mathbb{E}_t^{\mathbb{Q}}[e^{-r(\tau_j - t)}]$ and (ii) the cumulative risk-neutral default probability $G(A_t^R, V_t, T) = \mathbb{E}_t^{\mathbb{Q}}[\mathbb{1}_{\tau_j \leq T}]$ over the next T years. Using these two quantities, we are able to price any security issued by the firm. The Internet Appendix contains details about the estimation of $P_D(A_t^R, V_t)$ and $G(A_t^R, V_t, T)$ for a given set of structural parameters in our setup.[33]

To begin, we calculate the firm's debt value $B(A_t^R, V_t)$ as the present value of future coupon

[32] Applying Girsanov's theorem, we have $dW_t^{M\perp V} = dW_t^{M\perp V,\mathbb{Q}} - \xi_{M\perp V}\sqrt{V_t}dt$ and $dW_t^V = dW_t^{V,\mathbb{Q}} - \xi_V\sqrt{V_t}dt$.

[33] More precisely, our estimation strategy builds on Du et al. (2019) and Doshi et al. (2024) who develop a simulation approach to obtain the smooth mapping from a given pair of state variables (A_t^R, V_t) to $P_D(\cdot)$ and $G(\cdot, T)$ using two-dimensional Chebyshev polynomials.

payments plus the recovery value of the firm upon default:

$$B(A_t^R, V_t) = \frac{c^j}{r}\left(1 - P_D(A_t^R, V_t)\right) + (1-\alpha)A_D^j P_D(A_t^R, V_t), \tag{A.29}$$

where c_j is the coupon and α is the financial distress cost. For simplicity, we assume that firms have the same liquidation cost parameter. With leverage, a firm's value deviates from its unlevered counterpart A_t^R for two reasons. First, the firm enjoys tax benefits arising from its debt. If the tax rate is ζ, the present value of future tax shields is $\frac{\zeta c^j}{r}\left(1 - P_D(A_t^R, V_t)\right)$. However, this benefit comes with a cost. The debt exposes the firm to the risk of default, and the present value of future bankruptcy costs is $\alpha A_D^j P_D(A_t^R, V_t)$. Hence, the levered firm value can be expressed as:

$$L(A_t^R, V_t) = A_t^R + \frac{\zeta c^j}{r}\left(1 - P_D(A_t^R, V_t)\right) - \alpha A_D^j P_D(A_t^R, V_t).$$

Since the firm's equity is a residual claim, its value is calculated as the difference between the levered firm value and the debt value, $L(A_t^R, V_t) - B(A_t^R, V_t)$. It is given by:

$$S(A_t^R, V_t) = A_t^R - \frac{(1-\zeta)c^j}{r}\left(1 - P_D(A_t^R, V_t)\right) - A_D^j P_D(A_t^R, V_t). \tag{A.30}$$

This expression permits the straightforward calculation of the credit spread over T years, $CS(A_t^R, V_t, T)$.[34]

C Returns on corporate securities

To begin, consider an arbitrary corporate claim $f_t \equiv f(A_t^R, V_t)$ whose value is determined by the dynamics of the two state variables. According to Ito's lemma, its return dynamics under $\mathbb{P}$ satisfies the following stochastic differential equation:

$$\begin{aligned}
\frac{df_t}{f_t} &= \left(\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\right)\cdot\frac{dA_t^R}{A_t^R} + \left(\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\right)\cdot dV_t + \frac{1}{2}\left(\frac{\partial^2 f_t}{(\partial A_t^R)^2}\frac{(A_t^R)^2}{f_t}\right)\cdot\left(\frac{dA_t^R}{A_t^R}\right)^2 \\
&+ \frac{1}{2}\left(\frac{\partial^2 f_t}{(\partial V_t)^2}\frac{1}{f_t}\right)\cdot(dV_t)^2 + \left(\frac{\partial^2 f_t}{\partial A_t^R \partial V_t}\frac{A_t^R}{f_t^2}\right)\cdot\frac{dA_t^R}{A_t^R}\cdot dV_t \\
&= \mu_{f,t}dt + \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R\sqrt{V_t}dW_t^M + \frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\delta\sqrt{V_t}dW_t^V + \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\sigma_R dW_t^j,
\end{aligned} \tag{A.31}$$

[34] An alternative approach would be to compute a model-implied credit default swap (CDS) spread and rely on CDS spreads in the estimation. The two kinds of spreads are closely related both intuitively and by arbitrage restrictions (Duffie and Singleton, 2003).

where the drift of the process $\mu_{f,t}$ is given by

$$\begin{aligned}\mu_{f,t} &= \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}(r-q)+\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R(\mu_t-r)+\frac{\partial f_t}{\partial V_t}\frac{\kappa(\theta-V_t)}{f_t}+\frac{1}{2}\frac{\partial^2 f_t}{(\partial A_t^R)^2}\frac{(A_t^R)^2}{f_t}\left(\beta_R^2 V_t+\sigma_R^2\right)\\ &+ \frac{1}{2}\frac{\partial^2 f_t}{(\partial V_t)^2}\frac{V_t}{f_t}\delta^2+\frac{\partial^2 f_t}{\partial A_t^R\partial V_t}\frac{A_t^R V_t}{f_t}\rho\delta. \end{aligned}\tag{A.32}$$

The $\mathbb{P}$-dynamics described in equation (A.31) and the SDF defined in equation (4) suggest that the $\mathbb{Q}$-dynamics follows:

$$\frac{df_t}{f_t} = \mu_{f,t}^{\mathbb{Q}}dt+\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R\sqrt{V_t}dW_t^{M,\mathbb{Q}}+\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\delta\sqrt{V_t}dW_t^{V,\mathbb{Q}}+\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\sigma_R dW_t^j,$$

where the $\mathbb{Q}$-drift $\mu_{f,t}^{\mathbb{Q}}$ is expressed as

$$\begin{aligned}\mu_{f,t}^{\mathbb{Q}} &= \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}(r-q)+\frac{\partial f_t}{\partial V_t}\frac{\kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}}-V_t)}{f_t}+\frac{1}{2}\frac{\partial^2 f_t}{(\partial A_t^R)^2}\frac{(A_t^R)^2}{f_t}\left(\beta_R^2 V_t+\sigma_j^2\right)\\ &+ \frac{1}{2}\frac{\partial^2 f_t}{(\partial V_t)^2}\frac{V_t}{f_t}\delta^2+\frac{\partial^2 f_t}{\partial A_t^R\partial V_t}\frac{A_t^R V_t}{f_t}\rho\delta. \end{aligned}\tag{A.33}$$

From equations (A.32) and (A.33) combined with the no-arbitrage condition on the return on the tradeable position $\frac{df_t}{f_t}$ (i.e., $\mu_{f,t}^{\mathbb{Q}}=r$) implies that

$$\begin{aligned}\mu_{f,t}dt &= \frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R(\mu_t-r)dt+\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\kappa(\theta-V_t)dt+\mu_{f,t}^{\mathbb{Q}}dt-\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}}-V_t)dt\\ &= rdt+\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R(\mu_t-r)dt+\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\kappa(\theta-V_t)dt-\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}\mathbb{E}_t^{\mathbb{Q}}[dV_t]\end{aligned}\tag{A.34}$$

Combining the results in equations (2), (A.31), and (A.34), we get

$$\frac{df_t}{f_t}-rdt = \beta_{f,t}^A\left(\frac{dM_t}{M_t}-rdt\right)+\beta_{f,t}^V\left(dV_t-\mathbb{E}_t^{\mathbb{Q}}[dV_t]\right)+d\epsilon_{f,t},\tag{A.35}$$

where $\beta_{f,t}^A=\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\beta_R$, $\beta_{f,t}^V=\frac{\partial f_t}{\partial V_t}\frac{1}{f_t}$, and $d\epsilon_{f,t}=\frac{\partial f_t}{\partial A_t^R}\frac{A_t^R}{f_t}\sigma_R dW_t^j$ denotes the idiosyncratic risk of claim f_t.

Now, consider the market portfolio $M_{f,t}$ with N_M constituents with unit unlevered asset beta exposures $\beta_R = 1$. The returns on that portfolio must satisfy

$$
\begin{aligned}
\frac{dM_{f,t}}{M_{f,t}} &= \frac{1}{N_M}\sum_{j=1}^{N_M}\left(rdt + \beta^A_{f,t}\left(\frac{dM_t}{M_t} - rdt\right) + \beta^V_{f,t}\left(dV_t - \mathbb{E}^{\mathbb{Q}}_t\left[dV_t\right]\right) + \frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t}\sigma_R dW^j_t\right) \\
&= rdt + \beta^A_{f,t}\left(\frac{dM_t}{M_t} - rdt\right) + \beta^V_{f,t}\left(dV_t - \mathbb{E}^{\mathbb{Q}}_t\left[dV_t\right]\right) + \frac{1}{N_M}\sum_{j=1}^{N_M}\frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t}\sigma_R dW^j_t \\
&= rdt + \beta^A_{f,t}\left(\frac{dM_t}{M_t} - rdt\right) + \beta^V_{f,t}\left(dV_t - \mathbb{E}^{\mathbb{Q}}_t\left[dV_t\right]\right) + \left(\frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t}\sigma_R\right)\frac{1}{N_M}\sum_{j=1}^{N_M} dW^j_t \\
&= rdt + \beta^A_{f,t}\left(\frac{dM_t}{M_t} - rdt\right) + \beta^V_{f,t}\left(dV_t - \mathbb{E}^{\mathbb{Q}}_t\left[dV_t\right]\right), \qquad \text{(A.36)}
\end{aligned}
$$

where we have used the fact that $\beta^A_{f,t}$, $\beta^V_{f,t}$, and $\frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t}\sigma_R$ are homogeneous across firms and that $\frac{1}{N_M}\sum_{j=1}^{N_M} dW^j_t \xrightarrow{p} 0$ in the limit for the market portfolio.

We are now left in showing that $\beta^A_{M_f,t} = \beta^A_{f,t}$ and $\beta^V_{M_f,t} = \beta^V_{f,t}$. Since $M_{f,t} = f_t$, we have

$$
\frac{\partial M_{f,t}}{\partial A^R_t} = \frac{\partial f_t}{\partial A^R_t} \text{ and } \frac{1}{M_{f,t}} = \frac{1}{f_t} \Rightarrow \frac{\partial M_{f,t}}{\partial A^R_t}\frac{1}{M_{f,t}} = \frac{\partial f_t}{\partial A^R_t}\frac{1}{f_t}. \qquad \text{(A.37)}
$$

Given that $M_t = A^R_t$ is also true, we get

$$
\frac{\partial M_{f,t}}{\partial M_t}\frac{M_t}{M_{f,t}} = \frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t} \Rightarrow \beta^A_{M_f,t} = \beta^A_{f,t}. \qquad \text{(A.38)}
$$

A similar argument can be used to show that $\beta^V_{M_f,t} = \beta^V_{f,t}$. The same logic applies at the industry level but using the corresponding representative firm dynamics. We have

$$
\beta^A_{I_f,t} = \frac{\partial f_t}{\partial A^R_t}\frac{A^R_t}{f_t}\beta_R \text{ and } \beta^V_{I_f,t} = \beta^V_{f,t}, \qquad \text{(A.39)}
$$

given $I_t = A^R_t$ and $I_{f,t} = f_t$. Importantly, this implication does not rely on the diversification of idiosyncratic risk within the portfolio.

Therefore, knowing the dynamics of the representative firm in a given segment (market or industry) allows us to construct model-based predictions for the conditional risk premium of stock or corporate bond portfolio.

C.1 Construction of the aggregate asset and variance risk mimicking portfolios

Our tradeable factor mimicking portfolios are constructed from firm-level estimates of the model in Section 6, rather than from the market or industry representative firm in Sections 4 and 5. This approach allows us to exploit the richer cross-sectional heterogeneity in firm-level exposures.

D Market level likelihood

We estimate $\Theta \equiv \{\kappa, \theta, \delta, \rho, \xi_{M\perp V}, \xi_V, \sigma_R, c^R\}$ by maximizing the log-likelihood function, which is given by

$$\log \mathcal{L}(\Theta) = \sum_{t=2}^{T} \log \mathbb{P}\left(Y_t \mid Y_{t-1}; \Theta\right).$$

For ease of exposition, we split Y_t into two vectors: $Y_t^a = \left\{CS_{10,t}^m, \sigma_{M_S,t}^m\right\}$, which denotes the variables that are assumed to be accurately observed, and $Y_t^b = \left\{\sigma_{S,t}^m, \sigma_{M_B,t}^m, \sigma_{B,t}^m, Lev_t^m\right\}$, the vector of the remaining variables. By Bayes' rule, the transition probability of Y_t can be expressed as

$$\mathbb{P}\left(Y_t \mid Y_{t-1}; \Theta\right) = \mathbb{P}\left(Y_t^b \mid Y_t^a; \Theta\right) \times \mathbb{P}\left(Y_t^a \mid Y_{t-1}^a; \Theta\right). \tag{A.40}$$

We compute the two conditional probabilities in equation (A.40) individually. First, the probability of observing Y_t^b conditional on Y_t^a is equivalent to observing the measurement errors $\mathbf{e}_t$ in equation (19). This implies that the first conditional probability $\mathbb{P}\left(Y_t^b \mid Y_t^a; \Theta\right)$ is Gaussian and is given by

$$\mathbb{P}\left(Y_t^b \mid Y_t^a; \Theta\right) = \frac{1}{(2\pi)^{k/2}|\mathbf{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}\mathbf{e}_t^\top \mathbf{\Sigma}^{-1}\mathbf{e}_t\right)$$

Second, it is worth noting that observing $Y_t^{I,a}$ is equivalent to observing (A_t^R, V_t) or even (a_t^R, V_t) where $a_t^R \equiv \log\left(A_t^R\right)$. This result follows from the equality in equation (17) and the existence of a one-to-one mapping between the two state variables (a_t^R, V_t) and $Y_t^a = \{CS_{10,t}^m, \sigma_{M_S,t}^m\}$. Hence, the second conditional probability $\mathbb{P}\left(Y_t^a \mid Y_{t-1}^a; \Theta\right)$ is equal to the transition probability of (a_t^R, V_t) scaled by the absolute value of the Jacobian determinant of the mapping $(a_t^R, V_t) \mapsto Y_t^a$. It follows that

$$\mathbb{P}\left(Y_t^{I,a} \mid Y_{t-1}^{I,a}; \Theta\right) = \frac{1}{|\det(J_t)|} \times \mathbb{P}\left(a_t^R, V_t \mid a_{t-1}^R, V_{t-1}; \Theta\right),$$

where J_t denotes the Jacobian matrix

$$J_t = \begin{bmatrix} \frac{\partial CS_{10}(A_t^R, V_t; \Theta)}{\partial a_t^R} & \frac{\partial CS_{10}(A_t^R, V_t; \Theta)}{\partial V_t} \\ \frac{\partial \sigma_{M_S,t}(A_t^R, V_t; \Theta)}{\partial a_t^R} & \frac{\partial \sigma_{M_S,t}(A_t^R, V_t; \Theta)}{\partial V_t} \end{bmatrix}.$$

The transition probability of (a_t^R, V_t) can be further decomposed into

$$\mathbb{P}\left(a_t^R, V_t \mid a_{t-1}^R, V_{t-1}; \Theta\right) = \mathbb{P}\left(a_t^R \mid a_{t-1}^R, V_t, V_{t-1}; \Theta\right) \times \mathbb{P}\left(V_t \mid V_{t-1}; \Theta\right).$$

Since V_t follows a standard square-root process, its conditional distribution follows a noncentral chi-square distribution. Hence, $\mathbb{P}(V_t \mid V_{t-1}; \Theta)$ is calculated in closed-form in terms of a modified Bessel function. We are thus left with the estimation of $\mathbb{P}\left(a_t^R \mid a_{t-1}^R, V_t, V_{t-1}; \Theta\right)$.

To estimate it, we apply an Euler discretization scheme to the continuous-time dynamics of a_t^R:

$$\begin{aligned} a_t^R &= a_{t-1}^R + \left((r - q + (\mu_{t-1} - r) - \frac{1}{2}(V_{t-1} + \sigma_R^2)\right)\Delta t \\ &+ \sqrt{V_{t-1}}\left(\rho \Delta W_t^V + \sqrt{1-\rho^2}\Delta W_t^{M\perp V}\right) + \sigma_R \Delta W_t^j. \end{aligned}$$

Knowing a_{t-1}^R, V_t, and V_{t-1}, the conditional distribution of a_t^R is determined by two mutually independent normal random variables. (i) The Brownian shock $\Delta W_t^{M\perp V}$ follows a normal distribution $N(0, \Delta t)$. (ii) The Brownian shock ΔW_t^j follows a normal distribution $N(0, \Delta t)$. Since the linear combination of independent normal random variables is also normally distributed, $\mathbb{P}\left(a_t^R \mid a_{t-1}^R, V_t, V_{t-1}; \Theta\right)$ can be expressed using a Gaussian density function.

E Factor mimicking portfolios (FMP)

Aggregate asset risk

We first construct, for each firm j, a tradeable portfolio that is neutral with respect to variance risk and therefore loads purely on aggregate asset risk. At the beginning of each month t, we restrict attention to firms for which we observe both stock and bond returns and denote by $\mathcal{P}_t$ the set of firms. For each firm $j \in \mathcal{P}_t$, we first construct a pure-asset trading strategy defined by the long–short weights,

$$w_{S,j,t}^A = -\frac{\beta_{D,j,t}^V}{\beta_{S,j,t}^V - \beta_{D,j,t}^V}, \qquad w_{D,j,t}^A = 1 - w_{S,j,t}^A. \tag{A.41}$$

By construction, the variance exposure of the pure-asset strategy is

$$w_{S,j,t}^A \, \beta_{S,j,t}^V + w_{D,j,t}^A \, \beta_{D,j,t}^V = 0, \tag{A.42}$$

so that it has zero exposure to variance risk and a positive exposure to asset risk satisfying[35]

$$\beta^A_{Strat,j,t} = w^A_{S,j,t}\,\beta^A_{S,j,t} + w^A_{D,j,t}\,\beta^A_{D,j,t} = \frac{-\beta^V_{D,j,t}\;\beta^A_{S,j,t} + \beta^V_{S,j,t}\;\beta^A_{D,j,t}}{\beta^V_{S,j,t} - \beta^V_{D,j,t}} > 0, \tag{A.43}$$

as $-\beta^V_{D,j,t}\;\beta^A_{S,j,t} + \beta^V_{S,j,t}\;\beta^A_{D,j,t} > 0$, and $\beta^V_{S,j,t} - \beta^V_{D,j,t} > 0$.

The realized excess return on month $t+1$ of the firm-level pure-asset strategy is

$$R^A_{Strat,j,t+1} \;\equiv\; w^A_{S,j,t}\;R_{S,j,t+1} + w^A_{D,j,t}\;R_{D,j,t+1}. \tag{A.44}$$

where $R_{S,j,t+1}$ and $R_{D,j,t+1}$ denote the firm's stock and bond excess returns, respectively.

At the monthly frequency, we form tercile portfolios of these pure-asset firm strategies by sorting on $\beta^A_{Strat,j,t}$. Let $\mathcal{P}^A_{t,3}$ denote the set of firms in the top tercile at the start of month t, that is, the set of firms delivering a pure-asset strategy with the largest exposure to aggregate asset risk. The tercile-3 portfolio realized excess return, and betas are given by

$$R^A_{3,t+1} \;=\; \frac{1}{|\mathcal{P}^A_{t,3}|}\sum_{j\in\mathcal{P}^A_{t,3}} R^A_{Strat,j,t+1}, \tag{A.45}$$

$$\beta^A_{3,t} \;=\; \frac{1}{|\mathcal{P}^A_{t,3}|}\sum_{j\in\mathcal{P}^A_{t,3}} \beta^A_{Strat,j,t}. \tag{A.46}$$

We then define the aggregate asset risk mimicking portfolio by scaling the top tercile's return by its conditional (lagged) asset beta, $\beta^A_{P_3,t}$, to ensure a unit asset exposure:

$$R^A_{t+1} \;\equiv\; \frac{R^A_{3,t+1}}{\beta^A_{3,t}}. \tag{A.47}$$

The resulting aggregate asset FMP earns an annualized risk premium of 4.63%, with a Newey–West t-statistic of 2.54.

Aggregate variance risk

The aggregate variance risk mimicking portfolio combines firm-level stock and bond returns to have zero exposure to aggregate asset risk and unit exposure to aggregate variance risk. At the beginning of each month t, we restrict attention to firms for which we observe both stock and bond returns and denote by $\mathcal{P}_t$ this set of firms. For each firm $j \in \mathcal{P}_t$, we construct a

[35] Using firm leverage to combine stock and bond returns would recover the return on *levered* firm assets, which carries exposure to aggregate variance risk. The long–short weights above eliminate this variance component and isolate the asset-risk exposure.

pure-variance strategy with long–short weights

$$w^V_{S,j,t} \;=\; -\frac{\beta^A_{D,j,t}}{\beta^A_{S,j,t}-\beta^A_{D,j,t}}, \qquad w^V_{D,j,t} = 1 - w^V_{S,j,t}. \tag{A.48}$$

By construction, this strategy satisfies

$$w^V_{S,j,t}\,\beta^A_{S,j,t} + w^V_{D,j,t}\,\beta^A_{D,j,t} = 0, \tag{A.49}$$

so that it is asset-neutral (in theory) and loads negatively on aggregate variance risk:

$$\beta^V_{Strat,j,t} = w^V_{S,j,t}\,\beta^V_{S,j,t} + w^V_{D,j,t}\,\beta^V_{D,j,t} = \frac{-\beta^A_{D,j,t}\,\beta^V_{S,j,t} + \beta^A_{S,j,t}\,\beta^V_{D,j,t}}{\beta^A_{S,j,t}-\beta^A_{D,j,t}} < 0. \tag{A.50}$$

The realized excess return on the firm-level pure-variance strategy in month $t+1$ is

$$R^V_{Strat,j,t+1} = w^V_{S,j,t}\,R_{S,j,t+1} + w^V_{D,j,t}\,R_{D,j,t+1}, \tag{A.51}$$

where $R_{S,j,t+1}$ and $R_{D,j,t+1}$ denote the firm's stock and bond excess returns. Each month, we sort firms into terciles based on $\beta^V_{Strat,j,t}$ and let $\mathcal{P}^V_{t,1}$ denote the bottom tercile, which contains firms with the most negative variance exposures. Its realized return and average variance beta are

$$R^V_{1,t+1} \;=\; \frac{1}{|\mathcal{P}^V_{t,1}|}\sum_{j\in\mathcal{P}^V_{t,1}} R^V_{Strat,j,t+1}, \tag{A.52}$$

$$\beta^V_{1,t} \;=\; \frac{1}{|\mathcal{P}^V_{t,1}|}\sum_{j\in\mathcal{P}^V_{t,1}} \beta^V_{Strat,j,t}. \tag{A.53}$$

We scale the bottom-tercile return by its conditional variance beta to ensure unit variance exposure:

$$R^V_{t+1} = \frac{R^V_{1,t+1}}{\beta^V_{1,t}}. \tag{A.54}$$

While the model predicts negative comovement between aggregate asset and variance shocks, our empirical factor-mimicking portfolios approximate these shocks using firm-level exposures derived from filtered asset processes calibrated using industry-representative parameters rather than firm-specific structural estimates. This approximation induces a small positive loading of the variance FMP on the asset FMP (0.17). We therefore orthogonalize the variance FMP with respect to the asset FMP to isolate the incremental variance risk holding aggregate asset risk fixed, without altering the span of the relevant risk dimensions. As shown in Figure 7, the regression-based and model-implied exposures of stocks and DH corporate bonds line up closely across default-risk-sorted portfolios, indicating that the empirical factors capture the key risk dimensions implied by the model.

The resulting aggregate variance FMP earns an annualized risk premium of -2.29%, with a Newey–West t-statistic of -2.26.

Table 1: Summary statistics

Variable	Mean	SD	Min	Max	Skew	Kurt
Stock market excess return: $R_{M_S,t}$	9.57	17.15	−21.78	18.86	−0.56	5.47
Martin 2017: $SVIX_t$	4.97	4.44	0.90	35.87	3.15	17.17
Stock market volatility: $\sigma^m_{M_S,t}$	15.23	6.87	8.71	53.37	2.65	12.39
Rep. firm stock volatility: $\sigma^m_{S,t}$	29.25	6.48	20.83	56.81	1.34	5.09
DH corpo. bond market return: $R_{M_B,t}$	1.81	4.61	−10.52	5.34	−2.25	25.11
Rep. firm 10y credit spread: $CS^m_{10,t}$	179.66	80.60	60.92	633.61	2.58	13.21
DH corpo. bond market volatility: $\sigma^m_{M_B,t}$	3.51	2.64	1.78	21.36	4.11	23.83
Rep. firm DH corpo. bond volatility: $\sigma^m_{B,t}$	4.86	2.94	2.36	23.12	3.55	18.18
Leverage: Lev^m_t	0.45	0.04	0.37	0.61	0.58	3.43
Total firm debt ($ bill.)	18.72	4.87	7.02	27.16	−0.38	2.51

The table reports descriptive statistics for key market- and firm-level variables. The sample includes approximately 338 firms per month, corresponding to S&P 500 constituents with traded equity and outstanding corporate bonds. Reported variables include the stock market excess return ($R_{M_S,t}$), the lower bound of the expected stock market excess return from Martin (2017) defined as the squared-VIX ($SVIX_t$), the aggregate stock market volatility ($\sigma^m_{M_S,t}$), the representative firm's stock return volatility ($\sigma^m_{S,t}$), the duration-hedged corporate bond market excess return ($R_{M_B,t}$), the 10-year credit spread ($CS^m_{10,t}$), the duration-hedged corporate bond market volatility ($\sigma^m_{M_B,t}$), the representative firm's duration-hedged bond return volatility ($\sigma^m_{B,t}$), firm leverage (Lev^m_t), and total firm debt (in billions of U.S. dollars). For each variable, we report the time-series mean, standard deviation, minimum, maximum, skewness, and kurtosis. Stock and bond market returns are equally weighted excess (duration-adjusted) returns. Representative firm values are computed as equally weighted averages across individual firms. Bond returns are duration-hedged using duration-matched Treasury returns following Andreani et al. (2024). Detailed duration-adjusted notes are provided in Section IA.3 of the Internet Appendix. All variables are expressed in annualized units, except for the minimum and maximum of $R_{M_S,t}$ and $R_{M_B,t}$. Return and volatility measures are reported in percentages, and credit spreads are expressed in basis points. The sample period is 1997:01–2022:12.

Table 2: Model parameters and fit

Panel A: Model parameters		
Fixed parameters:	**Value**	**SE**
Asset payout rate (q) in %	2.00	
Corporate tax rate (ζ) in %	20.00	
Distress costs (α) in %	50.00	
Default barrier (A_D^R): 2/3 of total debt (in $billions)	12.48	
Risk-free rate (r) in %	1.87	
Estimated parameters:		
Mean reversion speed of systematic asset variance (κ)	2.82	[0.0636]
Long-run mean of systematic asset variance (θ) in %	0.72	[0.0000]
Volatility parameter for asset variance (δ) in %	10.19	[0.2095]
Correlation between asset value and variance shocks (ρ) in %	-30.61	[0.0253]
Market price of systematic variance risk (ξ_V)	-22.38	[0.2891]
Market price of asset-specific risk ($\xi_{M\perp V}$)	0.24	[5.4811]
Idiosyncratic volatility (σ_R) in %	1.38	[0.0038]
Coupon (c^R) in $	0.39	[0.0436]

Panel B: Model fit	**Data**		**Model**		**Corr.**
	Avg.	Std.	Avg.	Std.	
Variables observed accurately:					
10-year credit spread (bps)	179.66	80.60	179.72	80.57	–
Stock mkt. vol. (%)	15.23	6.87	15.33	6.85	–
Variables observed with errors:					
Rep. firm stock vol. (%)	29.25	6.45	27.24	6.44	0.80
DH corp. bond mkt. vol. (%)	3.51	2.64	3.40	1.57	0.79
Rep. firm DH corp. bond vol. (%)	4.86	2.94	5.73	1.57	0.86
Rep. firm leverage	0.45	0.04	0.44	0.06	0.72
Default probability:					
10-year physical default prob. (%)	2.65	–	1.50	2.01	–

Panel A reports the fixed and estimated parameters of the structural model. Fixed parameters are set, while the estimated parameters are obtained via maximum likelihood. Robust standard errors (Huber–White) appear in brackets and are expressed in the same units as the corresponding estimates. Panel B compares empirical ('Data') and model-implied ('Model') moments across key variables. Variables observed accurately are matched by construction, whereas those observed with errors are estimated by the model. The last column reports correlations between the data and model values. The panel further shows the model-implied 10-year physical default probability alongside the historical 10-year default rate for BBB-rated firms from Standard & Poor's (2022 annual report). The sample period is 1997:01–2022:12.

Table 3: In-sample predictive regression results for one-month-ahead market returns

	Stock market excess return			(DH) Corp. bond market return		
	Full sample	First half	Second half	Full sample	First half	Second half
Panel A: Model predictors $\widehat{\beta}^{A}_{M_Z,t}\widehat{\lambda}_{A,t} + \widehat{\beta}^{V}_{M_Z,t}\widehat{\lambda}_{V,t}$ ($Z = S$ stocks; $Z = B$ bonds)						
γ_0^{Model}	0.00	−0.07	0.06	−0.03	−0.05	−0.01
t-stat$_{\{H_0:\ \gamma_0=0\}}$	(0.09)	(−0.91)	(1.11)	(−1.96)	(−1.98)	(−0.75)
γ_1^{Model}	0.94	1.12	0.89	1.43	1.75	1.13
t-stat$_{\{H_0:\ \gamma_1=0\}}$	(1.82)	(1.60)	(2.23)	(3.23)	(2.60)	(4.56)
t-stat$_{\{H_0:\ \gamma_1=1\}}$	(−0.11)	(0.17)	(−0.26)	(0.97)	(1.12)	(0.52)
R^2_{Adj} (%)	1.60	2.61	0.53	6.76	9.80	3.67
R^2_{Theory} (%)	2.23	3.11	0.96	5.96	7.38	4.70
$\mathcal{W}$ p-value	[0.99]	[0.55]	[0.40]	[0.12]	[0.13]	[0.75]
Pricing errors when $\gamma_1^{Model} = 1$						
α_0^{Model}	−0.00	−0.05	0.05	−0.01	−0.02	−0.01
t-stat$_{\{H_0:\ \alpha_0=0\}}$	(−0.03)	(−0.86)	(1.30)	(−1.27)	(−1.12)	(−0.59)
Panel B: Benchmark predictors $SVIX_t$ (stocks) and $CS^m_{10,t}$ (bonds)						
$\gamma_0^{Bench.}$	0.04	0.06	−0.02	−0.05	−0.05	−0.14
t-stat$_{\{H_0:\ \gamma_0=0\}}$	(0.72)	(0.76)	(−0.35)	(−1.14)	(−0.99)	(−1.85)
$\gamma_1^{Bench.}$	1.00	−0.05	3.63	3.98	3.27	9.96
t-stat$_{\{H_0:\ \gamma_1=0\}}$	(0.64)	(−0.03)	(2.58)	(1.31)	(0.98)	(2.20)
t-stat$_{\{H_0:\ \gamma_1=1\}}$	(0.00)	(−0.58)	(1.87)	(0.98)	(0.68)	(1.98)
R^2_{Adj} (%)	0.24	−0.65	4.91	3.72	3.43	6.89
R^2_{Theory} (%)	0.31	−0.05	0.64	2.09	2.66	1.96
$\mathcal{W}$ p-value	[0.28]	[0.74]	[0.06]	[0.35]	[0.24]	[0.10]
Pricing errors when $\gamma_1^{Bench.} = 1$						
$\alpha_0^{Bench.}$	0.04	0.00	0.09	0.00	−0.00	0.00
t-stat$_{\{H_0:\ \alpha_0=0\}}$	(1.24)	(0.00)	(2.20)	(0.02)	(−0.22)	(0.50)

The table reports in-sample predictive regression results for one-month-ahead excess returns for the stock market and the duration-hedged (DH) corporate bond market. In Panel A, model-implied conditional risk premia are used as predictors. In Panel B, benchmark predictors are used: squared VIX for stock returns ($SVIX_t$) and the 10-year credit spread ($CS^m_{10,t}$) for corporate bond returns. Columns labeled 'Full sample,' 'First half,' and 'Second half' correspond to regressions run over the full sample and the two subsample periods, respectively. Reported statistics include the annualized intercept ($\gamma_0^{Model}/\gamma_0^{Bench.}$), slope ($\gamma_1^{Model}/\gamma_1^{Bench.}$), and their corresponding Newey–West t-statistics for various null hypotheses. Model fit is summarized by the adjusted R^2 (in percent) and by R^2_{Theory}, defined as the adjusted R^2 from a predictive regression imposing a zero intercept and a unit slope. The Wald test p-value for the joint null hypothesis $H_0 : \gamma_0 = 0,\ \gamma_1 = 1$ is computed using Newey–West. $\alpha_0^{Model}/\alpha_0^{Bench.}$ denotes the model/benchmark's annualized pricing error, defined as the difference between next month return and the model/benchmark conditional forecast. The 'Full sample' period is 1997:01–2022:12. The 'First half' and 'Second half' represent the first and second part of the sample, respectively.

Table 4: Out-of-sample predictive results for one-month-ahead market returns

	Model	$SVIX_t$	$CS^m_{10,t}$	Goyal & Welch Benchmark Predictors			
				Mean	Median	Mean$_{\geq 75}$	Mean$_{\geq 90}$
Panel A: Out-of-sample R^2_{OS} – Rolling mean benchmark							
Stock R^2_{OS} (%)	2.96	2.20	0.93	-4.03	-1.80	0.77	1.25
p-value	[0.054]	[0.027]	[0.012]	[0.381]	[0.275]	[0.097]	[0.045]
Bond R^2_{OS} (%)	8.33	-5.94	3.91	-4.15	-3.69	1.38	4.26
p-value	[0.048]	[0.282]	[0.110]	[0.481]	[0.381]	[0.331]	[0.136]
Panel B: Out-of-sample R^2_{OS} – Zero mean benchmark							
Stock R^2_{OS} (%)	2.97	2.22	0.95	-4.01	-1.78	0.78	1.27
p-value	[0.043]	[0.092]	[0.053]	[0.283]	[0.224]	[0.062]	[0.024]
Bond R^2_{OS} (%)	7.22	-7.78	2.24	-5.96	-5.49	-0.34	2.60
p-value	[0.035]	[0.327]	[0.121]	[0.531]	[0.541]	[0.491]	[0.255]

The table reports out-of-sample predictive results for one-month-ahead excess returns for the stock market and the duration-hedged (DH) corporate bond market. Panel A reports the out-of-sample R^2_{OS} values with a rolling 60-month mean as the benchmark, while Panel B reports the R^2_{OS} values with the zero mean benchmark. The columns labeled 'Model' correspond to the model-implied conditional risk premia as predictors, while '$SVIX_t$' and '$CS^m_{10,t}$' correspond to the squared VIX and 10-year credit spread, respectively. The columns 'Mean' and 'Median' report the mean and median of the R^2_{OS} values across all Goyal & Welch benchmark predictors. The columns 'Mean$_{\geq 75}$' and 'Mean$_{\geq 90}$' report the mean R^2_{OS} for predictors at or above the 75th and 90th percentiles, respectively. For the model, the out-of-sample (OS) forecasts are conducted using an initial training period of 5 years (60 months), after which forecasts are generated for the subsequent year. The training window is then expanded by one year, the model parameters are re-estimated accordingly, and forecasts are again computed for the following year. Reported statistics include the R^2_{OS} values expressed in percentage terms along with the associated Clark and West (2007) p-values. For the Goyal & Welch predictors we download all predictor data from Amit Goyal's website. We limit the set of predictors to those which match our empirical data spanning 1997:01–2022:12.

Table 5: Predictive regressions under alternative asset-pricing frameworks

	Reg.	CR1	CR2	CR3	Model
Stock/Bond Factor(s)	Asset	Asset	Asset	Asset	Asset+Variance
Stock/Bond Beta(s)	Cte	Condi.	Condi.	Condi.	Condi.
Asset/Variance Risk premium(s)	Condi.	Cte	Condi.	Condi.	Condi.
Filtered V_t	Return	None	Return	Model	Model
Panel A: Stock market excess return					
γ_0	(−0.07)	0.02	0.01	0.01	0.00
$t\text{-stat}_{\{H_0:\gamma_0=0\}}$	(−0.62)	(0.05)	(0.06)	(0.15)	(0.09)
γ_1	1.77	0.45	0.77	0.75	0.94
$t\text{-stat}_{\{H_0:\gamma_1=0\}}$	(1.39)	(0.15)	(0.72)	(1.85)	(1.81)
$t\text{-stat}_{\{H_0:\gamma_1=1\}}$	(0.60)	(−0.18)	(−0.21)	(−0.61)	(−0.11)
R^2_{Adj} (%)	0.71	(−0.29)	0.30	1.67	1.60
R^2_{Theory} (%)	1.15	(−0.80)	0.78	1.96	2.23
Panel B: (DH) Corporate bond market return					
γ_0	(−0.05)	(−0.23)	(−0.05)	(−0.03)	(−0.03)
$t\text{-stat}_{\{H_0:\gamma_0=0\}}$	(−1.29)	(−1.24)	(−1.32)	(−1.92)	(−1.96)
γ_1	3.96	7.86	2.88	2.05	1.43
$t\text{-stat}_{\{H_0:\gamma_1=0\}}$	(1.54)	(1.29)	(1.55)	(3.16)	(3.22)
$t\text{-stat}_{\{H_0:\gamma_1=1\}}$	(1.15)	(1.12)	(1.01)	(1.62)	(0.96)
R^2_{Adj} (%)	1.95	3.22	3.50	6.51	6.76
R^2_{Theory} (%)	1.30	0.51	2.43	5.25	5.96

The table reports in-sample predictive regression results for one-month-ahead excess returns for the stock market and the duration-hedged (DH) corporate bond market. Columns compare a reduced-form regression benchmark (Reg.), three credit-risk-based frameworks (CR1–CR3), and the fully specified structural model (Model). CR1 corresponds to a constant–aggregate-variance version of the structural model, estimated by maximum likelihood using the same observables and filtering unlevered asset value from the 10-year credit spread. Return forecasts for CR1 are constructed as the product of conditional market exposures and a constant aggregate asset risk premium. In CR2 and CR3, market exposures are taken from CR1 and combined with time-varying ('Condi.') aggregate asset risk premia. We consider two alternative measures of conditional aggregate variance to model time variation in asset risk premia. The first, labeled "Return," is obtained by filtering aggregate variance from the return on an aggregate asset factor-mimicking portfolio (FMP), constructed from firm-level stock and bond returns to achieve unit asset beta and zero exposure to aggregate variance risk (see Appendix E), using the estimated structural parameters from our model. The second, labeled "Model," corresponds to the variance path filtered directly from the structural model. The "Return"-based variance is used in Reg. and CR2, while the "Model"-based variance is used in CR3 and the full model. For specifications with TV asset risk premia, the aggregate asset risk premium parameter (the loading on V_t) is estimated by regressing the FMP return on the corresponding lagged filtered variance over the full sample. In contrast, unconditional market exposures in the regression benchmark are obtained by regressing stock or DH corporate bond excess returns on the FMP over the full sample. Reported statistics include the annualized intercept (γ_0) and slope (γ_1) coefficients, along with Newey–West t-statistics for the stated null hypotheses. Model fit is summarized by the adjusted R^2 (in percent) and by R^2_{Theory}, defined as the adjusted R^2 from a predictive regression imposing a zero intercept and a unit slope. The sample period is 1997:01–2022:12.

Table 6: Factor structure for stock and corporate bond markets

Panel A: Contemporaneous factor structure

	Stock Market	(DH) Corp. Bond Market
Alpha	0.02	−0.01
t-stat	(1.38)	(−0.74)
β^A	1.72	0.31
t-stat	(20.46)	(6.52)
β^V	0.21	−0.43
t-stat	(2.02)	(−4.85)
R^2_{Adj} (%)	87.12	57.82

Panel B: Predictive results for next-month hedged market returns

	Stock Market		(DH) Corp. Bond Market	
	VR Hedged	AR Hedged	VR Hedged	AR Hedged
γ_0^{Model}	0.00	0.01	−0.03	−0.02
t-stat$_{\{H_0:\ \gamma_0=0\}}$	(0.06)	(0.92)	(−2.22)	(−1.90)
γ_A^{Model} or γ_V^{Model}	0.98	−0.49	1.69	1.95
t-stat$_{\{H_0:\ \gamma_A \text{ or } \gamma_V=0\}}$	(2.00)	(−0.10)	(2.89)	(2.36)
t-stat$_{\{H_0:\ \gamma_A \text{ or } \gamma_V=1\}}$	(−0.05)	(−0.29)	(1.18)	(1.15)
R^2_{Adj} (%)	1.90	−0.32	4.79	3.18
	Pricing errors when γ_A^{Model} or $\gamma_V^{Model}=1$			
α_0^{Model}	0.00	0.02	−0.01	−0.01
t-stat$_{\{H_0:\ \alpha_0=0\}}$	(0.02)	(1.31)	(−1.20)	(−1.01)

The table presents contemporaneous regression results of stock and bond market returns on two factor-mimicking portfolios (FMPs) in Panel A, and predictive regression results for hedged market returns in Panel B. The aggregate asset FMP is the leverage-weighted average of stock and corporate bond market returns, while the aggregate variance FMP combines firm-level stocks and bonds to achieve zero asset beta and unit exposure to variance risk (see Appendix E). Panel A reports contemporaneous OLS regressions of stock and duration-hedged (DH) bond market returns on the two FMPs. Panel B presents predictive regressions of next-month stock and DH bond market returns hedged against either factor. Hedged returns are obtained by subtracting, from the excess or DH market return, the product of the full-sample beta (from Panel B) and the corresponding FMP realization. Panel B reports the intercept (γ_0^{Model}), predictive loadings (γ_A^{Model} for variance risk, VR hedged or γ_V^{Model} for asset risk, AR hedged). α_0^{Model} denotes the model's annualized pricing error, defined as the difference between the next month hedged return and the model-implied conditional asset or variance risk premium forecast. In all panels, the parameters' t-statistics are calculated using Newey-West, the adjusted R^2 values are in percent, and all estimates are annualized. The sample period is 1997:01–2022:12.

Table 7: Model goodness of fit by industry

	Panel A: Rep. firm stock vol.			**Panel B: Rep. firm DH bond vol.**			**Panel C: Rep. firm leverage**		
	Data avg.	Model avg.	Corr.	Data avg.	Model avg.	Corr.	Data avg.	Model avg.	Corr.
Business Equipment	35.49	30.23	0.54	5.21	4.52	0.84	0.31	0.28	0.59
Chemicals	26.08	23.72	0.76	3.74	3.82	0.79	0.32	0.30	0.34
Energy	34.87	32.39	0.71	6.25	7.18	0.79	0.41	0.34	0.43
Finance	29.08	27.01	0.87	4.65	6.52	0.83	0.68	0.62	0.24
Healthcare	27.81	31.79	0.43	4.13	4.91	0.65	0.28	0.29	0.25
Manufacturing	29.01	25.61	0.83	4.27	4.33	0.83	0.37	0.31	0.58
Shops	28.89	27.05	0.71	4.80	4.44	0.80	0.36	0.35	0.54
Telecommunications	30.38	28.35	0.49	6.24	5.20	0.78	0.48	0.45	0.72
Consumer non durables	24.50	23.83	0.70	4.01	3.95	0.80	0.34	0.32	0.72
Consumer durables	36.17	32.13	0.68	6.87	6.46	0.84	0.60	0.59	0.70
Utilities	23.01	21.16	0.65	5.49	4.70	0.79	0.62	0.61	0.68
Other	31.07	30.03	0.83	5.47	5.27	0.75	0.44	0.41	0.67
Average	29.70	27.78	0.68	5.09	5.11	0.79	0.43	0.41	0.54

The table evaluates the model's goodness of fit across twelve industries by comparing empirical ("Data") and model-implied ("Model") values for three representative firm-level variables: stock return volatility (Panel A), duration-hedged (DH) bond return volatility (Panel B), and financial leverage (Panel C). For each variable, the table reports the time-series average and the correlation between data and model-implied series. Structural parameters related to systematic risks, including prices of risk, are fixed at their market-level estimates (i.e., $\{\kappa, \theta, \delta, \rho, \xi_{M\perp V}, \xi_V\}$) as well as the filtered asset variance $\{V_t\}_{t\geq 0}$. For each industry, the representative firm's default barrier A_D^R is set to 2/3 of total debt from Table IA.III and the coupon (c^R), unlevered asset beta (β_R), and idiosyncratic risk (σ_R) are estimated. The representative firm's unlevered asset value (A_t^R) is filtered monthly to match the industry 10-year credit spread ($CS_{10,t}^I$). The model likelihood for each industry is defined over the three variables observed with noise described in each panel and the parameter estimates are reported in Table IA.IV. The sample period is 1997:01–2022:12.

Table 8: Model in-sample predictive performance for industry portfolio returns

	Panel A: Stocks					**Panel B: DH Corp. bonds**				
	γ_0^{Model}	γ_1^{Model}	$R^2_{Adj.}$	R^2_{Theory}	α_0^{Model}	γ_0^{Model}	γ_1^{Model}	$R^2_{Adj.}$	R^2_{Theory}	α_0^{Model}
Business	−0.03	1.51	1.74	2.11	0.02	−0.03	2.48	7.06	5.04	0.00
Equipment	(−0.52)	(2.77)			(0.34)	(−1.91)	(2.69)			(0.02)
Chemicals	−0.03	1.60	3.04	3.07	0.02	−0.02	1.37	4.60	4.54	−0.01
	(−0.52)	(2.53)			(0.67)	(−1.43)	(3.03)			(−0.90)
Energy	0.02	0.84	0.22	0.84	0.00	−0.06	2.19	4.83	3.75	−0.01
	(0.24)	(1.77)			(0.01)	(−1.93)	(2.95)			(−0.82)
Finance	0.01	0.87	1.16	1.76	−0.00	−0.03	1.18	5.71	4.94	−0.02
	(0.16)	(1.17)			(−0.06)	(−1.62)	(2.26)			(−1.51)
Health	0.04	0.95	0.68	0.93	0.03	−0.01	1.75	3.29	3.22	0.00
Care	(0.91)	(1.96)			(1.10)	(−0.78)	(2.19)			(0.30)
Manufacturing	−0.01	1.19	1.68	2.26	0.01	−0.02	1.25	3.49	3.55	−0.01
	(−0.18)	(1.84)			(0.15)	(−1.17)	(2.42)			(−0.91)
Shops	0.01	1.12	1.67	2.22	0.01	−0.02	1.83	4.95	4.37	−0.01
	(0.10)	(2.37)			(0.42)	(−1.49)	(2.54)			(−0.49)
Telecom-	−0.03	1.13	2.01	2.59	−0.01	−0.05	2.92	8.03	5.03	−0.00
munications	(−0.47)	(2.61)			(−0.26)	(−2.10)	(3.20)			(−0.03)
Consumer	0.05	0.39	0.06	−0.21	−0.00	−0.03	1.73	5.83	4.80	−0.01
Non-Durables	(1.29)	(0.99)			(−0.11)	(−1.76)	(2.90)			(−1.12)
Consumer	0.02	0.03	−0.32	−3.73	−0.10	−0.04	1.31	1.53	1.16	−0.03
Durables	(0.26)	(0.06)			(−1.48)	(−1.70)	(1.48)			(−1.17)
Utilities	0.06	0.28	−0.05	−1.19	−0.02	−0.04	1.72	5.22	4.40	−0.01
	(1.49)	(0.79)			(−0.42)	(−2.04)	(2.96)			(−1.10)
Other	−0.00	1.15	1.80	2.36	0.01	−0.04	2.36	6.34	4.71	−0.00
	(−0.03)	(1.91)			(0.30)	(−1.96)	(2.91)			(−0.23)
Average	0.01	0.92	1.14	1.08	−0.00	−0.03	1.84	5.07	4.13	−0.01

The table reports predictive regression results for one-month-ahead excess returns on the stock and DH corporate bond industry portfolios. Panel A uses model-implied conditional risk premia for industry stock portfolios as predictors, while Panel B reports results for DH corporate bond portfolios. Reported statistics include the annualized intercept (γ_0^{Model}) and slope (γ_1^{Model}) coefficients in the first row for each industry, with Newey–West t-statistics reported in parentheses below. α_0^{Model} denotes the model's annualized pricing error, defined as the difference between the next month return and the model-implied conditional forecast. The Newey–West t-statistics test the null hypothesis that the corresponding coefficient equals zero. Model fit is summarized by the adjusted $R^2_{Adj.}$ (%) and by R^2_{Theory} (%), defined as the adjusted R^2 from a predictive regression imposing a zero intercept and a unit slope. The last row of the table reports the average parameters and R-squared. The sample period is 1997:01–2022:12.

Table 9: Risk premium decomposition of industry portfolios

	Panel A: Stocks			**Panel B: DH Corp. bonds**		
	Total risk premium	Asset risk premium	Variance risk premium	Total risk premium	Asset risk premium	Variance risk premium
Business Equipment	9.27	9.27	0.00	2.13	1.37	0.77
Chemicals	8.66	8.67	0.00	2.20	1.38	0.83
Energy	10.37	10.75	−0.38	3.74	2.35	1.39
Finance	10.05	11.10	−1.06	3.97	2.57	1.40
Healthcare	7.02	7.02	0.00	1.69	1.09	0.60
Manufacturing	9.38	9.44	−0.06	2.59	1.57	1.01
Shops	8.57	8.58	0.00	2.24	1.39	0.85
Telecommunications	10.44	10.45	−0.01	2.65	1.87	0.79
Consumer Non-Durables	8.96	8.97	−0.01	2.50	1.45	1.05
Consumer Durables	12.21	12.43	−0.22	2.92	2.31	0.60
Utilities	10.53	10.71	−0.18	3.19	2.26	0.93
Other	9.49	9.48	0.00	2.42	1.63	0.79
Average	9.58	9.74	−0.16	2.69	1.77	0.92

The table reports the time-series average of the conditional total risk premium for stock and duration-hedged (DH) corporate bond industry portfolios. It also presents the decomposition of the total risk premium into the asset risk premium component and the variance risk premium component. Panel A reports the results for stocks, while Panel B presents the results for bonds. The sample period is 1997:01–2022:12.

Table 10: In-sample predictive regression results for one-month-ahead firm-level returns

	Model	HKM	FF5	IPCA			
				n_F=2	n_F=3	n_F=5	n_F=10
Panel A: Stocks							
γ_0	0.00	0.00	−0.00	0.00	0.00	0.00	0.00
$t\text{-stat}_{\{H_0:\gamma_0=0\}}$	(0.33)	(0.01)	(−0.14)	(0.24)	(0.17)	(0.28)	(0.50)
γ_1	0.90	1.07	1.13	0.93	0.96	0.88	0.69
$t\text{-stat}_{\{H_0:\gamma_1=0\}}$	(1.91)	(3.22)	(3.18)	(3.00)	(2.96)	(2.35)	(2.10)
$t\text{-stat}_{\{H_0:\gamma_1=1\}}$	(−0.22)	(0.22)	(0.36)	(−0.24)	(−0.11)	(−0.33)	(−0.94)
$\mathcal{W}$ p-value	[0.95]	[0.97]	[0.94]	[0.97]	[0.99]	[0.95]	[0.56]
R^2_{Adj} (%)	0.69	0.14	0.13	0.06	0.06	0.05	0.04
R^2_{Theory} (%)	0.68	0.14	0.12	0.06	0.06	0.04	0.03
R^2_{Pred} (%)	1.48	0.94	0.93	0.87	0.87	0.85	0.83
Panel B: Corporate Bonds							
γ_0	−0.00	0.00	0.00	0.00	0.00	0.00	−0.00
$t\text{-stat}_{\{H_0:\gamma_0=0\}}$	(−2.14)	(0.39)	(0.46)	(0.58)	(0.51)	(0.16)	(−0.21)
γ_1	1.66	0.92	0.91	0.81	0.81	0.84	0.87
$t\text{-stat}_{\{H_0:\gamma_1=0\}}$	(3.78)	(4.52)	(4.74)	(5.35)	(5.53)	(5.42)	(5.11)
$t\text{-stat}_{\{H_0:\gamma_1=1\}}$	(1.50)	(−0.41)	(−0.45)	(−1.27)	(−1.31)	(−1.03)	(−0.74)
$\mathcal{W}$ p-value	[0.10]	[0.69]	[0.64]	[0.08]	[0.12]	[0.42]	[0.75]
R^2_{Adj} (%)	2.85	0.61	0.59	0.51	0.48	0.44	0.41
R^2_{Theory} (%)	2.31	0.60	0.58	0.48	0.45	0.41	0.38
R^2_{Pred} (%)	2.79	1.09	1.07	0.97	0.94	0.90	0.87

The table presents in-sample predictive results for one-month-ahead excess stock returns and duration-adjusted (DH) corporate bond returns at the firm-level. Panel A (B) reports the results for stocks (DH corporate bonds). The column labeled 'Model' corresponds to the model-implied conditional risk premia as predictors. The columns $n_F = 2$, 3, 5, and 10 are the models estimated via IPCA with differing number of latent factors. The factors are instrumented with the Kelly et al. (2023) 29 stock and bond characteristics and a constant. The 'HKM' column is the He et al. (2017) two-factor model, which includes the stock market and traded intermediary capital factor. The 'FF5' column is the original Fama and French (1993) five-factor model, which includes the Fama-French three-factors and the DEF and $TERM$ factors. These models are also estimated via the IPCA methodology as pre-specified, observable factors, instrumented with the same 29 characteristics and a constant. The IPCA conditional expected return forecasts for asset class f are defined as, $\lambda^{\text{IPCA}}_{f,j,t+1} \equiv z'_{i,t}\left(\widehat{\Gamma}_{\alpha,f}+\widehat{\Gamma}_{\beta,f}\,\widehat{\mu}_f\right)$, where the Γs are estimated via IPCA, $z_{i,t}$ are the characteristics and $\widehat{\mu}_f$ are the time-series averages of the traded factors (their risk premiums). The γ_0 and γ_1 coefficients are the constant and slope coefficients from regressions of the realized stock or bond returns on the predicted expected return values from the estimated models. R^2_{Adj} is the R-squared from this regression, R^2_{Pred} and R^2_{Theory} are defined as: $R^2_{Pred} = 1-\sum_{j,t}\left(R_{f,j,t+1}-(\gamma_0+\gamma_1\lambda_{f,j,t})\right)^2/\sum_{j,t}R^2_{f,j,t+1}$, and $R^2_{Theory} = 1-\left[\sum_{i,t}\left(R_{f,j,t+1}-\lambda_{f,j,t}\right)^2/(N-k)\right]/\left[\sum_{j,t}\left(R_{f,j,t+1}-\bar{R}\right)^2/(N-1)\right]$, respectively. The sample period is 1998:12–2022:12

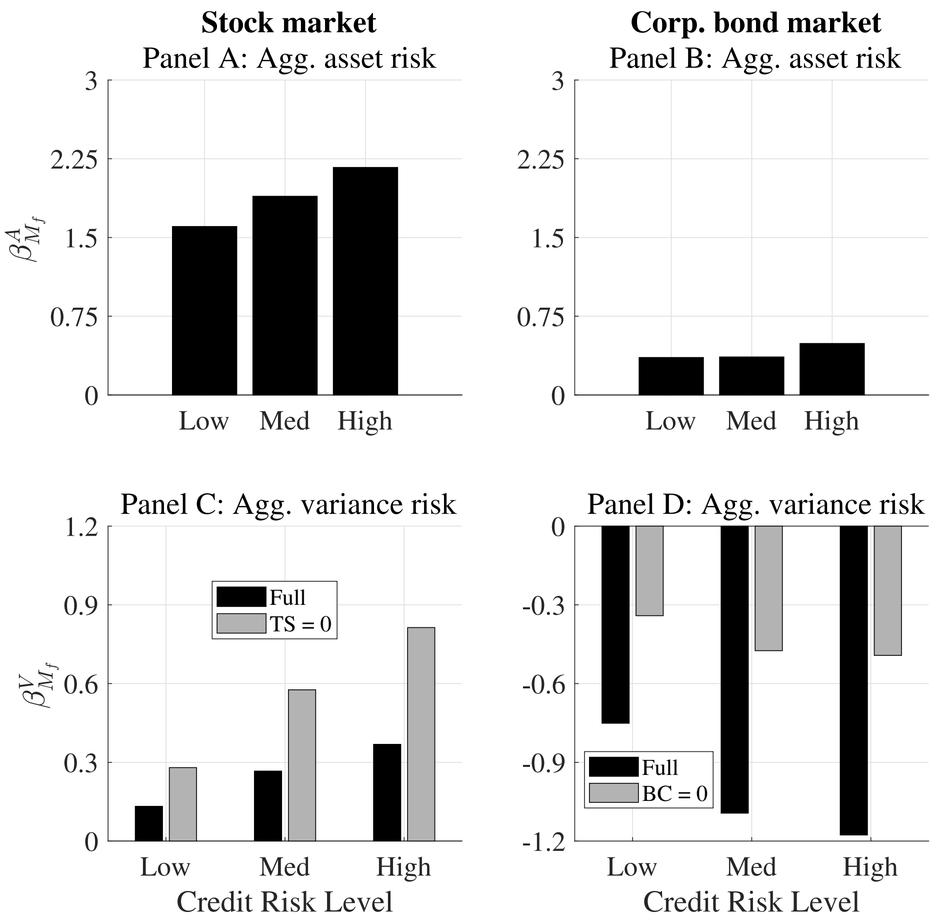

Figure 1: Model-implied exposures.

This figure reports the model-implied exposures of the aggregate stock and corporate bond markets to asset and variance risk across three credit-risk levels. The left (right) panels display results for equity (bond) market portfolios. For each, their representative firms are categorized into low-, medium-, and high-default-risk based on 10-year credit spreads of 99.06 bps, 179.66 bps, and 260.26 bps, respectively. To compute these exposures, we use the estimated structural parameters from Section 4.3, fix V_t at its long-run mean $\hat{\theta}$, and solve for the asset value that matches each spread level. Panels A and B report elasticities with respect to aggregate asset risk, and Panels C and D report elasticities with respect to aggregate variance risk. These exposures correspond to

$$\beta^A_{M_f,t} \equiv \frac{\partial M_{f,t}}{\partial M_t}\frac{M_t}{M_{f,t}}, \qquad \beta^V_{M_f,t} \equiv \frac{\partial M_{f,t}}{\partial V_t}\frac{1}{M_{f,t}},$$

as defined in Proposition 1. Panels C and D also decompose the variance-risk exposures. For equities, black bars report full model variance betas; and light-gray bars report exposures when the tax shield is set to zero ($\zeta = 0$). For corporate bonds, black bars again show full model variance betas; and light-gray bars report exposures when bankruptcy costs are set to zero ($\alpha = 0$). Model-estimation details appear in Section 4.2, and variable construction is described in Internet Appendix IA.1.

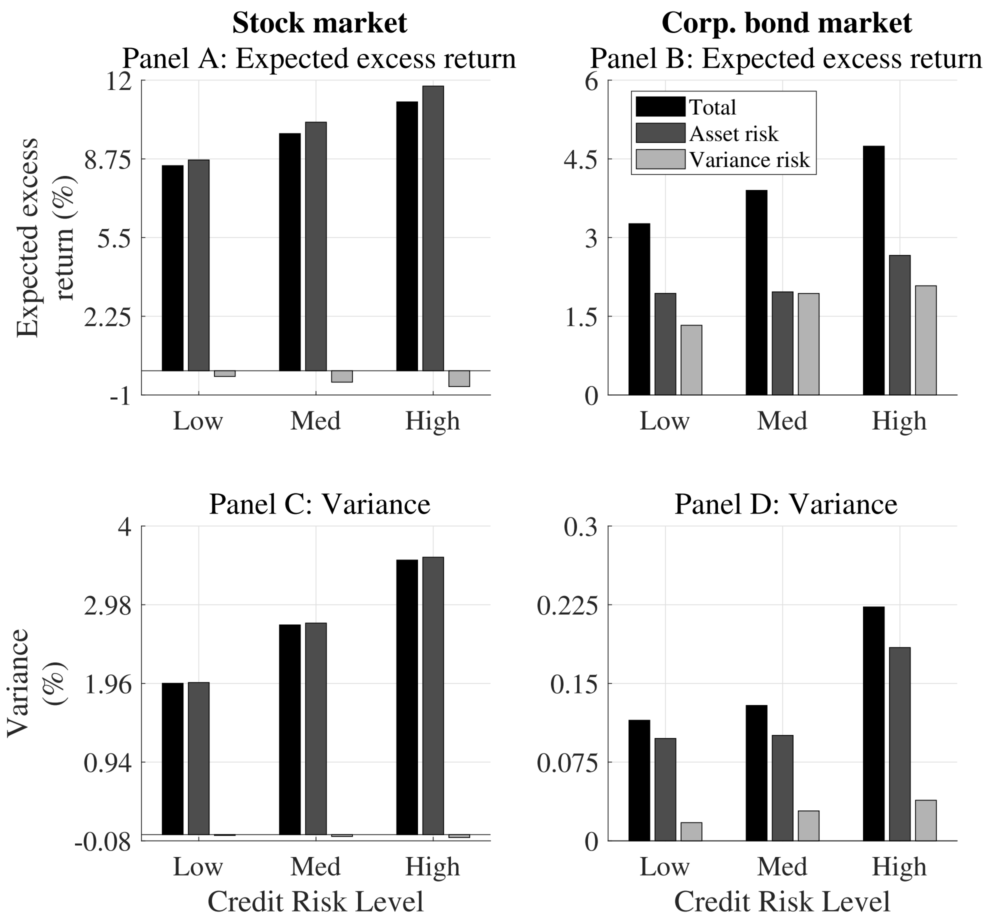

Figure 2: Model-implied expected excess returns, and variances.

This figure shows model-implied elasticities, expected excess returns, and return variances for stock and corporate bond market portfolios across credit risk levels (low to high). Left (right) panels display results for stocks (bonds). Each panel reports model predictions for portfolios of representative firms with low, medium, or high default risk, corresponding to 10-year credit spreads of 99.06 bps, 179.66 bps, and 260.26 bps, respectively. To generate these results, we use the estimated structural parameters from Section 4.3, fixing V_t at $\hat{\theta}$ and solve for the asset value that matches each spread level. Panels A and B show the expected excess return and its decomposition into asset and variance risk premia. Panels C and D present total variance, similarly decomposed. Model estimation is discussed in Section 4.2 and details on variable computation appear in Internet Appendix IA.1.

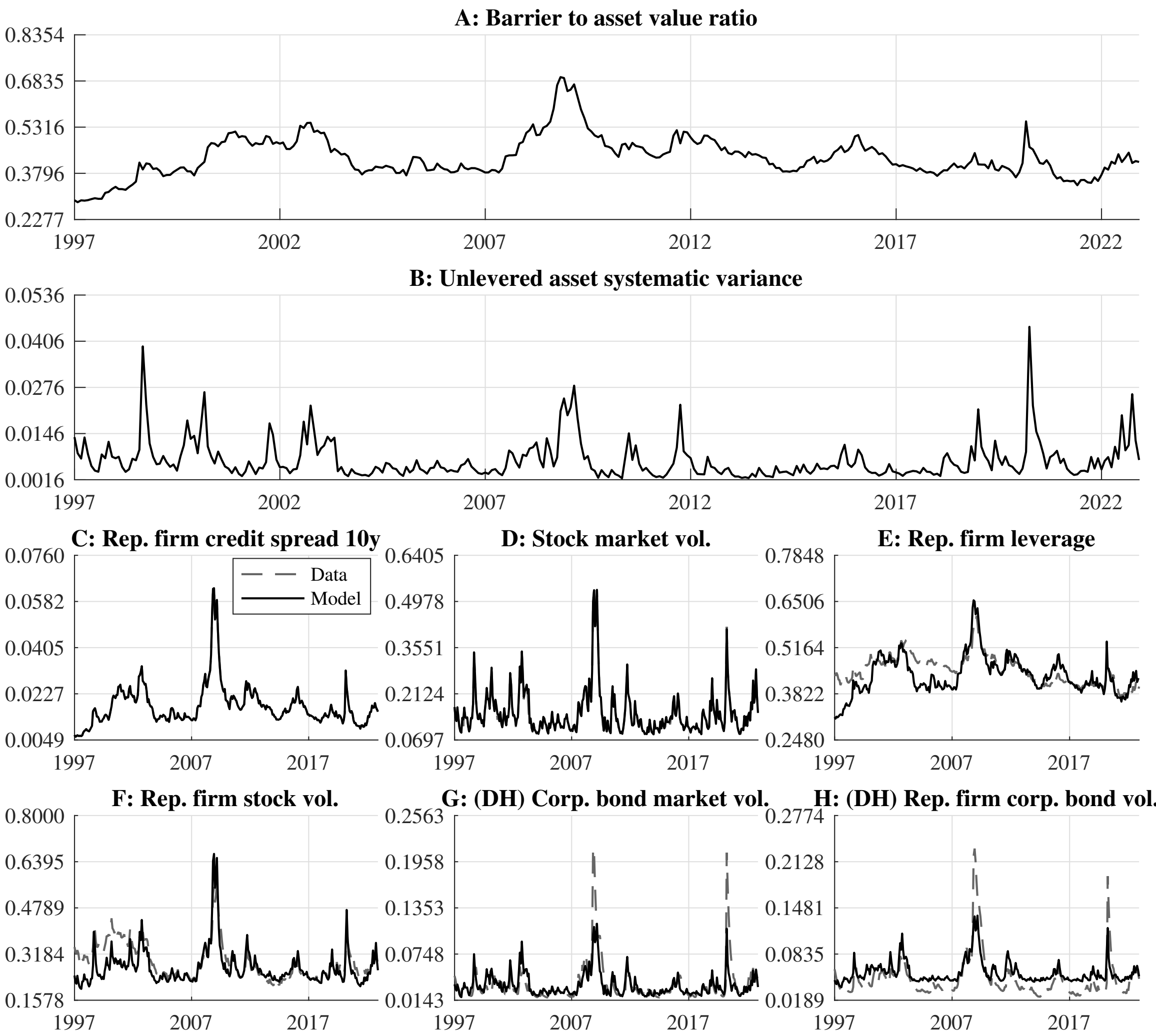

Figure 3: Market level estimation results.

The figure plots the time-series of filtered states and model variables. Panel A shows the ratio of the default barrier to filtered unlevered assets of the representative firm, while Panel B presents the filtered asset systematic variance. Panels C and D show the 10-year credit spread and stock market conditional volatility, which are assumed to be observed accurately and are exactly matched by the model. Panels E to H display both the 'Data' variables (dashed grey lines) and the 'Model' variables (solid dark grey lines) for the representative firm's leverage (E) and stock volatility (F), the DH corporate bond market volatility (G), and the representative firm's DH bond volatility (H). The sample period is 1997:01–2022:12.

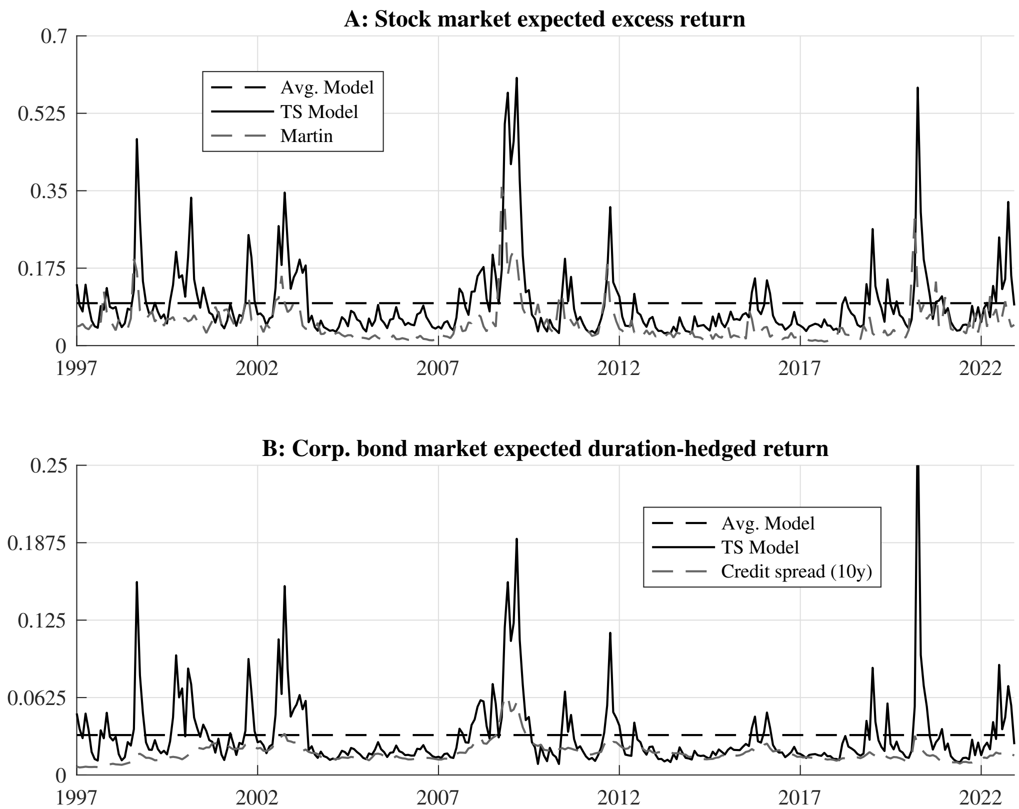

Figure 4: Conditional stock and duration hedged (DH) bond market risk premia.
The figure plots the time series of conditional risk premia for the stock market (Panel A) and the duration hedged (DH) bond market (Panel B). In each panel, the solid dark grey line represents the model-implied risk premium, the dashed dark grey horizontal line indicates the model's sample average, and the dashed light grey line shows the benchmark. For stocks, we use the squared VIX as a proxy for the lower bound of expected excess returns (Panel A), while for DH bond expected returns, we use the 10-year credit spread as a benchmark (Panel B). The sample period is 1997:01–2022:12.

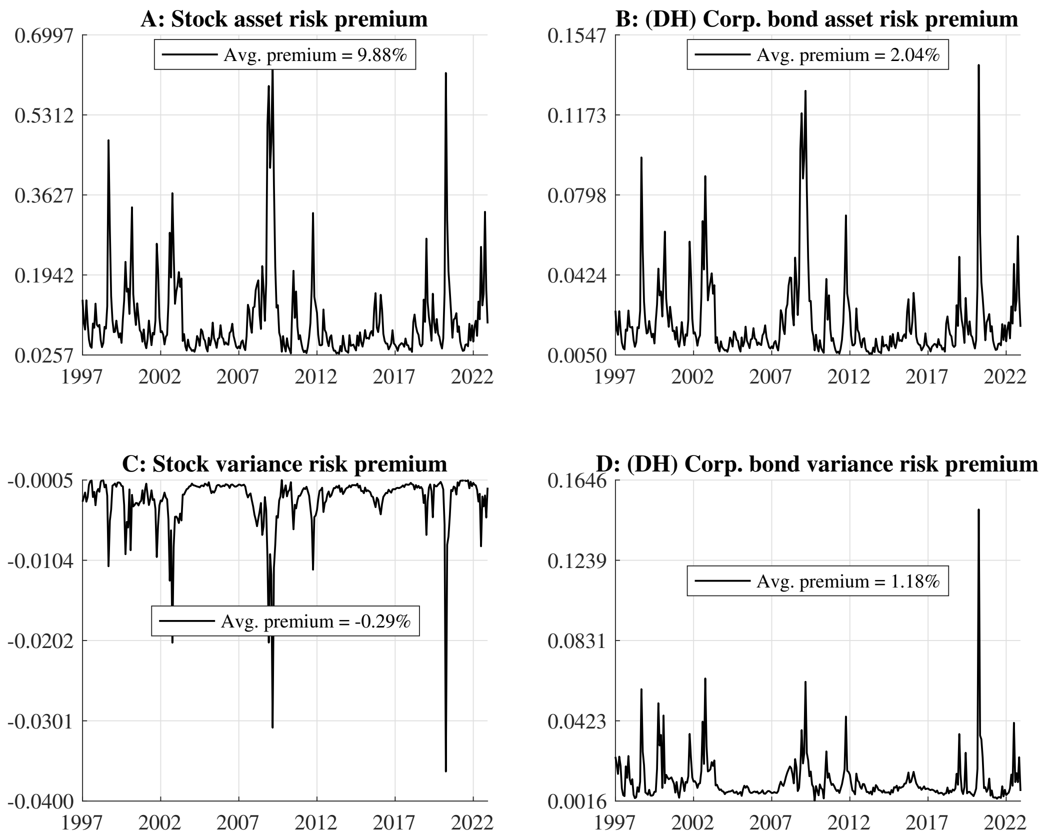

Figure 5: Decomposition of stock and DH bond risk premia.

The figure shows the time-series of conditional asset and variance risk premia for the stock market (Panels A and C) and the duration hedged (DH) bond market (Panels B and D). Panels A and B present the conditional asset risk premia for each market, while Panels C and D display the corresponding conditional variance risk premia. The sample period is 1997:01–2022:12.

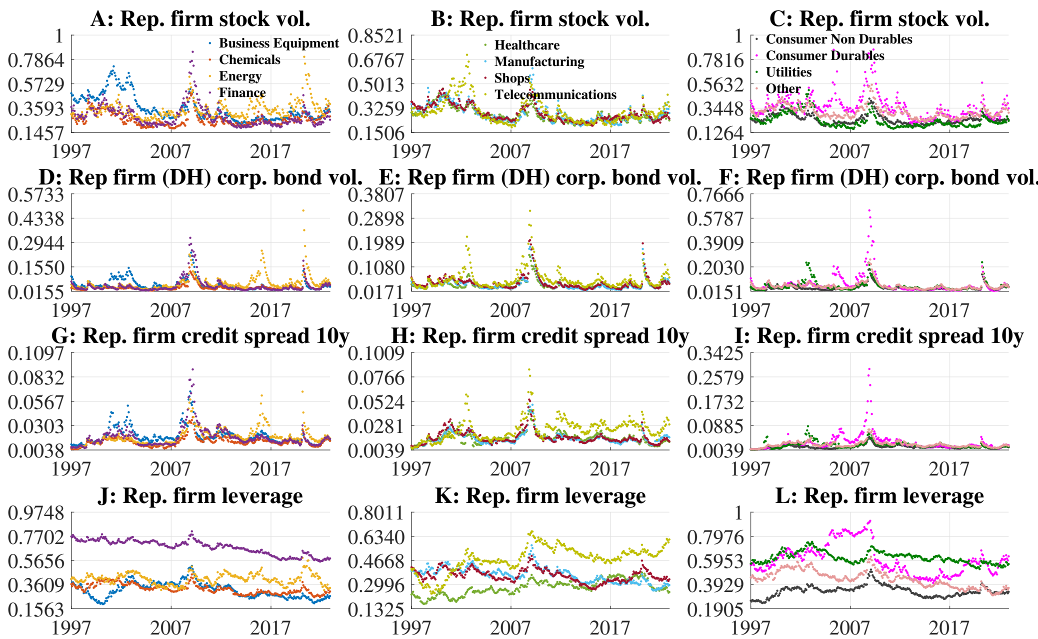

Figure 6: Industry representative firm 'Data' variables.

The figure shows the time-series of each industry representative firm's stock volatility (Panels A to C), duration hedged (DH) corporate bond volatility (Panels D to F), 10-year credit spread (Panels G to I), and leverage (Panels J to L). Industries are divided into three groups and are identified by distinct colors, as indicated in the legend in Panels A to C. Panels in a given vertical column present the results for the same industry group. The sample period is 1997:01–2022:12.

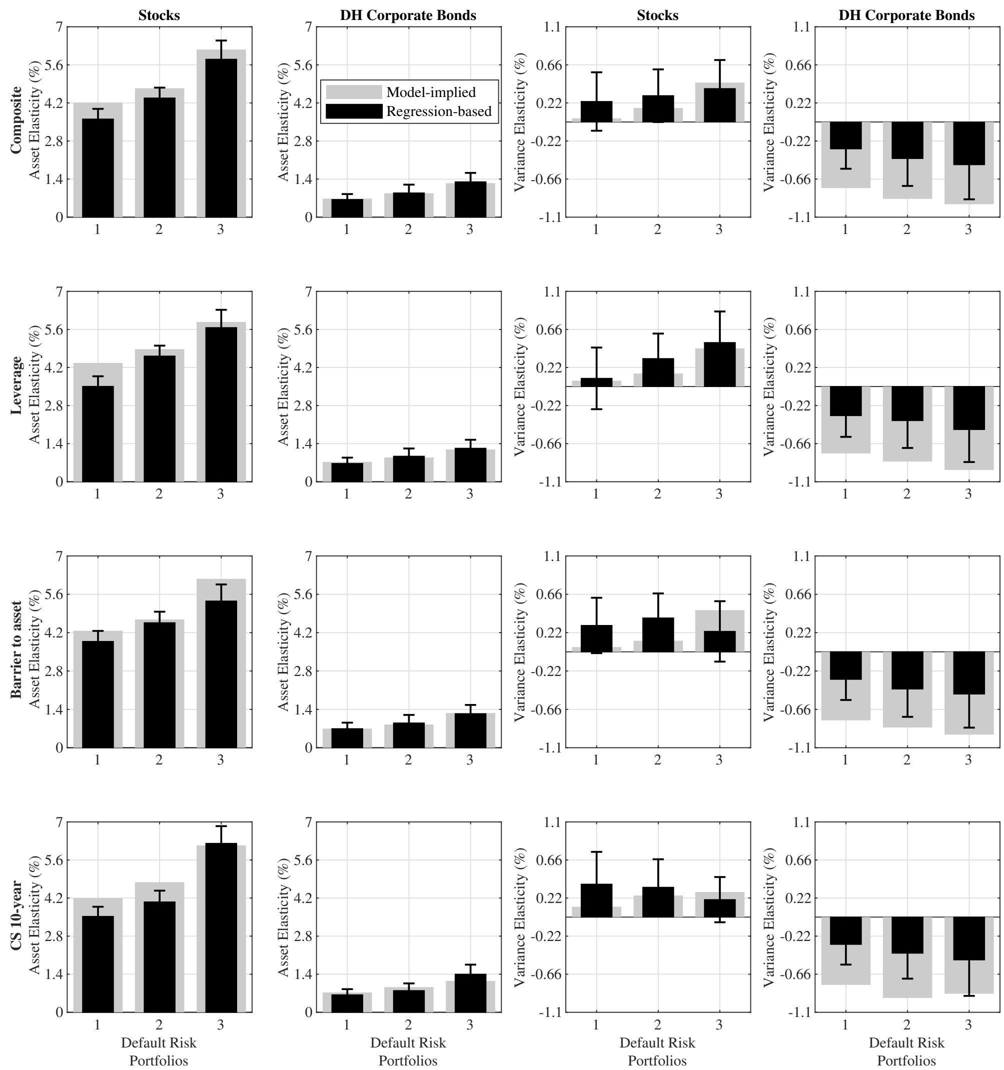

Figure 7: Empirical and model elasticities of sorted portfolios across default risk measures

This figure reports the estimated elasticities of stock and duration-hedged (DH) corporate bond returns to aggregate asset and variance risk factors for portfolios sorted on firm default risk. The aggregate asset factor mimicking portfolio (FMP) combines firm-level stocks and bonds to attain unit exposure to asset risk and zero exposure to variance risk, while the aggregate variance FMP attains zero asset-risk exposure and unit variance-risk exposure (see Appendix E). Each month, firms are independently sorted into five portfolios based on one of four conditioning default-risk variables: (i) leverage, (ii) the model barrier-to-filtered-asset ratio, (iii) the 10-year credit spread, and (iv) a composite index defined as the average of the three z-scored characteristics. Rows correspond to these four conditioning variables, while columns display the resulting exposures for stocks (left panels) and DH corporate bonds (right panels), separately for asset-risk elasticities in percent and variance-risk elasticities. Portfolio returns are formed by equally weighting firm-level excess (or DH) returns within each portfolio. Empirical elasticities (black bars) are computed as the product of regression-based exposures with a given FMP volatility. Exposures are estimated using full-sample time-series regressions of portfolio excess/DH returns on the two aggregate FMPs, with Newey–West 95% confidence intervals shown as vertical lines. Model-implied exposures (light-gray bars) are constructed by first computing, for each month, the average firm-level exposures within each portfolio—namely the model-implied sensitivities of returns to aggregate asset and variance risks. These monthly portfolio-level elasticities are then averaged across time and scaled by the corresponding volatility of the asset- and variance-FMP returns. The sample period is 1997:01–2022:12.

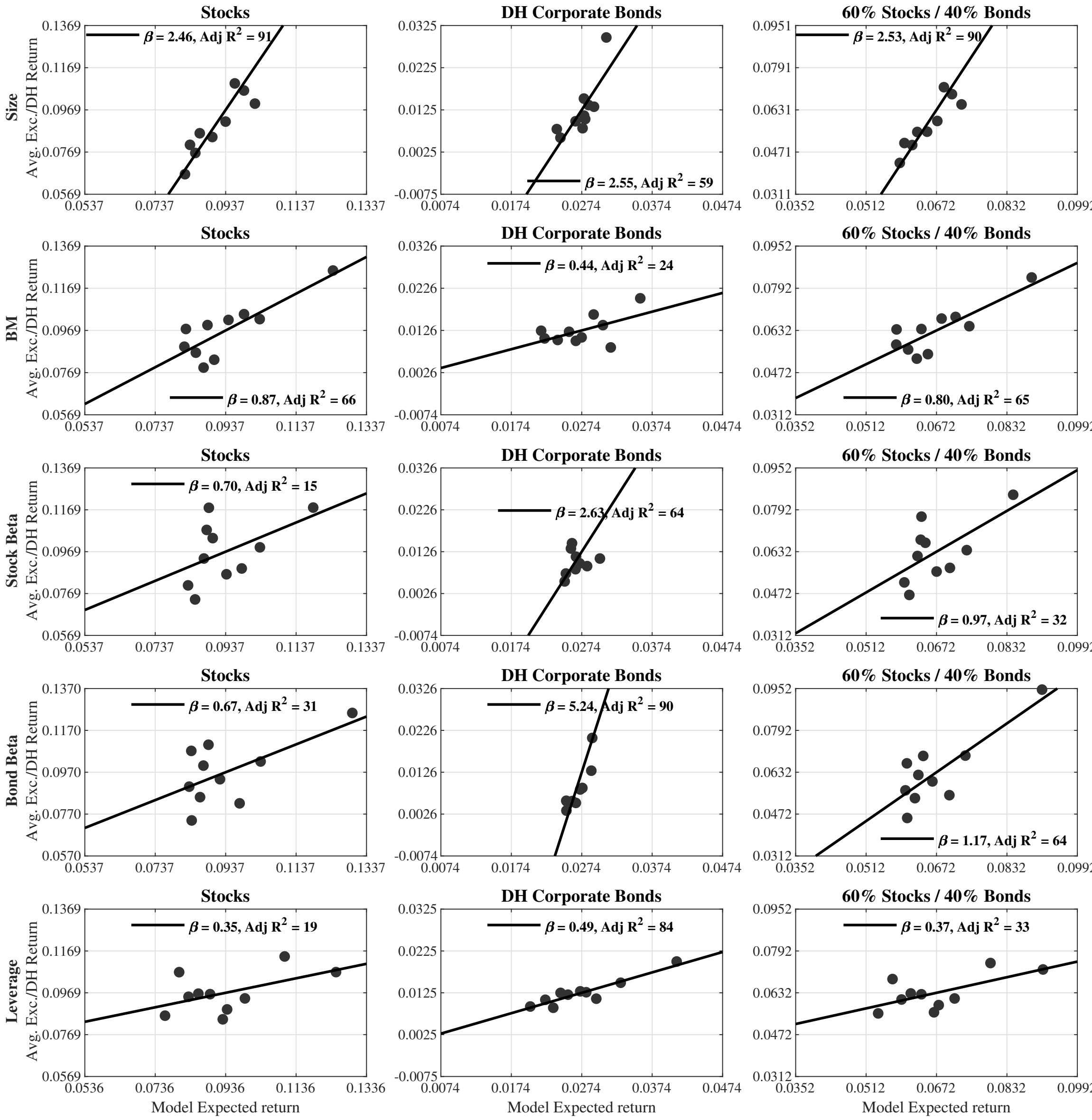

Figure 8: Cross-sectional fit between average realized and model-implied expected returns across firm characteristics.

The figure presents the cross-sectional fit between average realized portfolio returns and model-implied expected returns across firm characteristics. Firms are sorted each month into ten portfolios based on six conditioning variables—size, book-to-market, stock beta, bond beta, and leverage—and portfolio-level average realized returns and model-implied expected excess returns are computed over time. Each row corresponds to a different conditioning variable, while each column reports results for stocks (left), duration-hedged corporate bonds (middle), and a 60/40 equity–bond combination (right). Within each panel, average realized portfolio returns are plotted against the corresponding model-implied expected returns, along with the fitted cross-sectional regression line. The cross-sectional β-slope and adjusted R-squared in percentage points summarize the model's pricing performance for a given conditioning variable and asset class. The sample period is 1997:01–2022:12.

Internet Appendix for:

The Risk and Return of Stocks and Bonds

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Abstract

This Internet Appendix provides additional information, tables, figures, and empirical results supporting the main text.

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IA.1 Computing model variables

The first step toward computing corporate security prices, CS spreads, index values, and option prices is to estimate the present value of a dollar received at default $P_D(A_t^R, V_t) = \mathbb{E}_t^{\mathbb{Q}}\left[e^{-r(\tau_R - t)}\right]$ and the cumulative risk-neutral default probability over the next T years $G(A_t^R, V_t, T) = \mathbb{E}_t^{\mathbb{Q}}\left[1_{\tau_r \leq T}\right]$. To achieve this, we first discretize the Q-dynamics of the two state variables A_t^R and V_t. Then, for a given combination of the state variables on the grid $\left\{A_{grid}^R, V_{grid}\right\}$, we use the discretized dynamics to simulate the representative firm's future asset values. From the simulated paths, we calculate $\hat{P}_D(A_{grid}^R, V_{grid})$ as $\hat{\mathbb{E}}_t^{\mathbb{Q}}\left[e^{-r\tau_R}\right] = \frac{1}{MC}\sum_{mc=1}^{MC} e^{-r\tau_R^{mc}}$, where $\tau_R^{mc} = \inf\left\{s \geq 0 : A_s^{R,mc} \leq A_D^j\right\}$. Here, $A_s^{R,mc}$ represents the asset value at time s for simulated path mc, and MC denotes the number of Monte Carlo simulations. The cumulative risk-neutral default probability over any horizon T can be computed as $\hat{G}(A_{grid}^R, V_{grid}, T) = \hat{\mathbb{E}}_t^{\mathbb{Q}}\left[\mathbb{1}_{\tau_R \leq T}\right] = \frac{1}{MC}\sum_{mc=1}^{MC} \mathbb{1}_{\tau_R^{mc} \leq T}$.

We repeat this simulation exercise for every combination of the state variables on the grid. This gives us an entire cross-section of P_D as a function of the initial state variables. We project this cross-section onto the Chebyshev basis matrix and estimate the loadings. The estimated Chebyshev loadings provide a smooth mapping from the two state variables and P_D, in other words, $(A_t^R, V_t) \mapsto P_D(A_t^R, V_t)$. Similarly, we estimate the Chebyshev loadings for the mapping between the two state variables and the cumulative risk-neutral default probability $(A_t^R, V_t) \mapsto G(A_t^R, V_t, T)$ for a given T. Using the two sets of Chebyshev loadings, we can compute the price of any corporate security, including equity and debt as well as CS as functions of the two state variables.

IA.2 Industry level likelihood

This appendix outlines the likelihood function employed to estimate the structural parameters and asset value dynamics of the representative firm within a given industry.

For consistency, our industry-level estimation takes as given the dynamics of systematic risks, $\hat{\Theta}_M \equiv \{\hat{\kappa}, \hat{\theta}, \hat{\delta}, \hat{\rho}, \hat{\xi}_{M\perp V}, \hat{\xi}_V\}$ and $\{\hat{V}_t\}_{t\geq 0}$, obtained from the market-level estimation. We estimate the remaining parameter set $\Theta_I \equiv \{\beta_R, \sigma_R, c^R\}$ by maximizing the log-likelihood function, which is given by

$$\log \mathcal{L}(\Theta_I) = \sum_{t=2}^{T} \log \mathbb{P}\left(Y_t^I \mid Y_{t-1}^I; \{\Theta_I, \hat{\Theta}_M\}\right).$$

We split Y_t^I into $Y_t^{I,a} = \left\{CS_{10,t}^I\right\}$, which is assumed to be accurately observed, and $Y_t^{I,b} = \left\{\sigma_{S,t}^I, \sigma_{B,t}^I, Lev_t^I\right\}$, the vector of the remaining variables. By Bayes' rule, the transition probability of Y_t^I can be expressed as

$$\mathbb{P}\left(Y_t^I \mid Y_{t-1}^I; \{\Theta_I, \hat{\Theta}_M\}\right) = \mathbb{P}\left(Y_t^{I,b} \mid Y_t^{I,a}; \{\Theta_I, \hat{\Theta}_M\}\right) \times \mathbb{P}\left(Y_t^{I,a} \mid Y_{t-1}^{I,a}; \{\Theta_I, \hat{\Theta}_M\}\right). \tag{IA.55}$$

We compute the two conditional probabilities in equation (IA.55) individually. First, the probability of observing $Y_t^{I,b}$ conditional on $Y_t^{I,a}$ is equivalent to observing the measurement errors $\mathbf{e}_t$:

$$\text{Rep. firm stock vol.:} \left(\sigma_{S,t}^I - \sigma_S(A_t^R, \hat{V}_t; \{\Theta_I, \hat{\Theta}_M\})\right) \cdot \left(\sigma_{S,t}^I\right)^{-1} = \quad e_t^S \tag{IA.56}$$

$$\text{Rep. firm corp. bond DH vol.:} \left(\sigma_{B,t}^I - \sigma_B(A_t^R, \hat{V}_t; \{\Theta_I, \hat{\Theta}_M\})\right) \cdot \left(\sigma_{B,t}^I\right)^{-1} = \quad e_t^B \tag{IA.57}$$

$$\text{Rep. firm Lev.:} \left(Lev_t^I - Lev(A_t^R, \hat{V}_t; \{\Theta_I, \hat{\Theta}_M\}\right) \cdot \left(Lev_t^I\right)^{-1} = \quad e_t^{Lev}, \tag{IA.58}$$

where $\mathbf{e}_t \sim N(0, \Sigma)$ with $\mathbf{e}_t$ denoting the 3 by 1 vector of errors. This implies that the first conditional probability $\mathbb{P}\left(Y_t^{I,b} \mid Y_t^{I,a}; \{\Theta_I, \hat{\Theta}_M\}\right)$ is Gaussian and is given by

$$\mathbb{P}\left(Y_t^{I,b} \mid Y_t^{I,a}; \{\Theta_I, \hat{\Theta}_M\}\right) = \frac{1}{(2\pi)^{k/2}|\mathbf{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}\mathbf{e}_t^\top \mathbf{\Sigma}^{-1}\mathbf{e}_t\right)$$

Second, it is worth noting that observing $Y_t^{I,a}$ is equivalent to observing (A_t^R) or even (a_t^R) where $a_t^R \equiv \log\left(A_t^R\right)$ after conditioning on $\hat{V}_t$. This result follows from the fact that we filter A_t^R from $CS_{10,t}^I$ conditioning on $\hat{V}_t$ and the existence of a one-to-one mapping between the state variable (a_t^R) and $Y_t^{I,a} = \{CS_{10,t}^I\}$ once $\hat{V}_t$ is fixed. Hence, the second conditional probability $\mathbb{P}\left(Y_t^{I,a} \mid Y_{t-1}^{I,a}; \{\Theta_I, \hat{\Theta}_M\}\right)$ is equal to the transition probability of (a_t^R) scaled by the absolute value of the Jacobian determinant of the mapping $(a_t^R) \mapsto Y_t^{I,a}$. It follows that

$$\mathbb{P}\left(Y_t^{I,a} \mid Y_{t-1}^{I,a}; \{\Theta_I, \hat{\Theta}_M\}\right) = \frac{1}{|J_t|} \times \mathbb{P}\left(a_t^R, \hat{V}_t \mid a_{t-1}^R, \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right),$$

where J_t denotes the Jacobian matrix

$$J_t = \frac{\partial CS_{10}(A_t^R, \hat{V}_t; \{\Theta_I, \hat{\Theta}_M\})}{\partial a_t^R}.$$

The transition probability of $(a_t^R, \hat{V}_t)$ can be further decomposed into

$$\mathbb{P}\left(a_t^R, \hat{V}_t \mid a_{t-1}^R, \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right) = \mathbb{P}\left(a_t^R \mid a_{t-1}^R, \hat{V}_t, \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right) \times \mathbb{P}\left(\hat{V}_t \mid \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right).$$

where $\mathbb{P}\left(\hat{V}_t \mid \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right)$ is calculated in closed-form in terms of a modified Bessel function. We are thus left with the estimation of $\mathbb{P}\left(a_t^R \mid a_{t-1}^R, \hat{V}_t, \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right)$.

To estimate it, we apply an Euler discretization scheme to the continuous-time dynamics of a_t^R:

$$\begin{aligned} a_t^r &= a_{t-1}^r + \left((r - q + \beta_R(\hat{\mu}_{t-1} - r) - \frac{1}{2}(\beta_R^2 \hat{V}_{t-1} + \sigma_R^2)\right)\Delta t \\ &+ \beta_R \sqrt{\hat{V}_{t-1}}\left(\hat{\rho}\Delta\hat{W}_t^V + \sqrt{1-\rho^2}\Delta W_t^{M\perp V}\right) + \sigma_R \Delta W_t^j. \end{aligned}$$

Knowing a_{t-1}^R, $\hat{V}_t$, and $\hat{V}_{t-1}$, the conditional distribution of a_t^R is determined by two mutually independent normal random variables as $\hat{W}_t^V$ can be filtered from the variance path estimated. (i) The aggregate Brownian shock $\Delta W_t^{M\perp V}$ follows a normal distribution $N(0, \Delta t)$. (ii) The firm-specific Brownian shock ΔW_t^j follows a normal distribution $N(0, \Delta t)$. Note that $\Delta W_t^{M\perp V}$ represents an aggregate shock that is not separately identified in the market-level estimation. Its distribution must therefore be explicitly integrated into the estimation procedure at the industry level. Since the linear combination of independent normal random variables is also normally distributed, $\mathbb{P}\left(a_t^R \mid a_{t-1}^R, \hat{V}_t, \hat{V}_{t-1}; \{\Theta_I, \hat{\Theta}_M\}\right)$ can be expressed using a Gaussian density function.

IA.3 Duration-adjusted corporate bond returns

Let $r_{B,i,j,t}$ denote the total return on corporate bond i of firm j in month t,

$$r_{B,i,j,t} = \frac{B_{i,j,t} + AI_{i,j,t} + C_{i,j,t}}{B_{i,j,t-1} + AI_{i,j,t-1}} - 1, \tag{IA.59}$$

where $B_{i,j,t}$ is the clean price, $AI_{i,j,t}$ is accrued interest, and $C_{i,j,t}$ is the coupon payment, if any.

Following Andreani, Palhares, and Richardson (2024), we construct a duration-matched Treasury portfolio for each corporate bond. Let $\text{EDUR}_{i,j,t}$ denote the bond's effective duration. Consider a fixed grid of Treasury key-rate durations $\mathcal{D} = \{d_1, \ldots, d_K\}$ (e.g., $1, 2, 5, 7, 10, \ldots$ years). For a given bond and month, choose $d_L, d_H \in \mathcal{D}$ such that $d_L \leq \text{EDUR}_{i,j,t} \leq d_H$ and define the weights

$$w_{L,i,j,t} = \frac{d_H - \text{EDUR}_{i,j,t}}{d_H - d_L}, \qquad w_{H,i,j,t} = \frac{\text{EDUR}_{i,j,t} - d_L}{d_H - d_L}, \tag{IA.60}$$

so that $w_{L,i,j,t} + w_{H,i,j,t} = 1$.

Let $r_{d,t}^{\text{TSY}}$ denote the return in month t on the zero-coupon Treasury with duration d. The duration-matched Treasury return for bond i of firm j is then

$$r_{\mathrm{RATES},i,j,t} = w_{L,i,j,t}\, r^{\mathrm{TSY}}_{d_L,t} + w_{H,i,j,t}\, r^{\mathrm{TSY}}_{d_H,t}. \tag{IA.61}$$

For example, if $\mathrm{EDUR}_{i,j,t} = 3$, $d_L = 2$, and $d_H = 5$, then

$$r_{\mathrm{RATES},i,j,t} = r^{\mathrm{TSY}}_{2\mathrm{Y},t}\left(\frac{5-3}{5-2}\right) + r^{\mathrm{TSY}}_{5\mathrm{Y},t}\left(\frac{3-2}{5-2}\right),$$

.

Our duration-hedged corporate bond return is defined as the total bond return net of the duration-matched Treasury portfolio,

$$R_{B,i,j,t} = r_{B,i,j,t} - r_{\mathrm{RATES},i,j,t}. \tag{IA.62}$$

The results are not sensitive to methodological choices related to the duration-adjustment. In robustness, we also implement the duration-adjustment method of van Binsbergen, Nozawa, and Schwert (2025), which leads to very similar results.

IA.4 IPCA Latent Factor Estimation

We estimate an Instrumented Principal Component Analysis (IPCA) model with an intercept, following Kelly, Pruitt, and Su (2019). Let $R_{f,j,t+1}$ denote the excess return on asset class f of firm j in month $t+1$, where $R_{f,j,t+1}$ is either the excess stock return or the duration-hedged corporate bond return $R_{B,j,t+1}$, indexed generically by $j = 1, \ldots, N_M$. Let $z_{j,t}$ be the $L \times 1$ vector of 29 stock and corporate bond characteristics from Kelly et al. (2023) observed at time t, including a constant.

The IPCA model with intercept specifies

$$R_{f,j,t+1} = \alpha_{f,j,t} + \beta_{f,j,t}^{\top} F_{t+1} + \varepsilon_{f,j,t+1}, \tag{IA.63}$$

$$\alpha_{f,j,t} = z_{j,t}^{\top}\Gamma_{\alpha,f}, \qquad \beta_{f,j,t} = z_{j,t}^{\top}\Gamma_{\beta,f}, \tag{IA.64}$$

where F_{t+1} is a $n_F \times 1$ vector of latent factors, $\Gamma_{\alpha,f}$ is an $L \times 1$ vector of intercept coefficients, $\Gamma_{\beta,f}$ is an $L \times n_F$ matrix of slope coefficients, and $\varepsilon_{f,j,t+1}$ is an idiosyncratic error.

Stacking assets into the $N_M \times 1$ return vector $R_{f,t+1}$ and the $N_M \times L$ characteristic matrix Z_t, the model can be written compactly as

$$R_{f,t+1} = Z_t\Gamma_{\alpha,f} + Z_t\Gamma_{\beta,f}F_{t+1} + \varepsilon_{f,t+1}. \tag{IA.65}$$

Equivalently, define $\tilde{F}_{t+1} = (1, F_{t+1}^\top)^\top$ and $\tilde{\Gamma} = [\Gamma_{\alpha,f},\, \Gamma_{\beta,f}]$, so that

$$R_{f,t+1} = Z_t \tilde{\Gamma} \tilde{F}_{t+1} + \varepsilon_{f,t+1}. \tag{IA.66}$$

Parameters and factors are obtained by minimizing the sum of squared residuals

$$\min_{\Gamma_{\alpha,f}, \Gamma_{\beta,f}, \{F_{t+1}\}_{t=1}^{T-1}} \sum_{t=1}^{T-1} \left\| R_{f,t+1} - Z_t \Gamma_{\alpha,f} - Z_t \Gamma_{\beta,f} F_{t+1} \right\|^2. \tag{IA.67}$$

Conditional on $(\Gamma_{\alpha,f}, \Gamma_{\beta,f})$, the latent factors solve a cross-sectional regression of returns net of alpha on dynamic betas,

$$F_{t+1} = \left(\Gamma_{\beta,f}^\top Z_t^\top Z_t \Gamma_{\beta,f} \right)^{-1} \Gamma_{\beta,f}^\top Z_t^\top \left(R_{f,t+1} - Z_t \Gamma_{\alpha,f} \right), \qquad t = 1, \ldots, T-1. \tag{IA.68}$$

Conditional on $\{F_{t+1}\}$, the coefficients $(\Gamma_{\alpha,f}, \Gamma_{\beta,f})$ are obtained from a stacked least-squares regression of $R_{f,t+1}$ on Z_t and $Z_t F_{t+1}$. We iterate between these two steps (alternating least squares) until convergence.

To identify the factor space we impose the normalization $\Gamma_{\beta,f}^\top \Gamma_{\beta,f} = I_K$ and require the factors to have diagonal covariance with non-increasing diagonal elements. To separate intercepts from risk loadings, we further impose $\Gamma_{\alpha,f}^\top \Gamma_{\beta,f} = 0_{1\times K}$, so that the component of expected returns spanned by the characteristics and aligned with $\Gamma_{\beta,f}$ is attributed to risk exposures rather than to alpha. We estimate this model separately for stocks and bonds, considering specifications with $n_F = 2$ (to align with our two-factor model) and $n_F = 5$ latent factors.

IA.4.1 Instrumented Observable Factor Models

We also consider pre-specified factor models nested within the IPCA framework, instrumented with the same $L = 29$ characteristics. Let G_{t+1} be an $M \times 1$ vector of traded observable factors. We focus on two specifications: (i) the He, Kelly, and Manela (2017) two-factor intermediary capital model with the stock market factor and the traded intermediary capital factor, $G_{t+1}^{\text{HKM}} = (\text{MKTS}_{t+1}, \text{CPTLT}_{t+1})'$; and (ii) a two-factor liquidity model with traded stock and bond liquidity factors constructed following Pastor and Stambaugh (2003), $G_{t+1}^{\text{ILLIQ}} = (\text{ILLIQ}_{t+1}^S, \text{ILLIQ}_{t+1}^B)'$.

For contingent claim f of firm j we specify

$$R_{f,j,t+1} = \alpha_{f,j,t} + \beta_{f,j,t}^\top F_{t+1} + \delta_{f,j,t}^\top G_{t+1} + \varepsilon_{f,j,t+1}, \tag{IA.69}$$

$$\alpha_{f,j,t} = z_{j,t}^\top \Gamma_{\alpha,f}, \qquad \beta_{f,j,t} = z_{j,t}^\top \Gamma_{\beta,f}, \qquad \delta_{f,j,t} = z_{j,t}^\top \Gamma_{\delta,f}, \tag{IA.70}$$

where F_{t+1} is a $n_F \times 1$ vector of latent IPCA factors, G_{t+1} is the $M \times 1$ vector of observable traded factors (either G_{t+1}^{HKM} or G_{t+1}^{ILLIQ}), $\Gamma_{\alpha,f}$ is an $L \times 1$ vector of intercept coefficients, and $\Gamma_{\beta,f}$ and $\Gamma_{\delta,f}$ are $L \times n_F$ and $L \times M$ characteristic–loading matrices, respectively.

Stacking assets, the model can be written as

$$R_{f,t+1} = Z_t\Gamma_{\alpha,f} + Z_t\Gamma_{\beta,f}F_{t+1} + Z_t\Gamma_{\delta,f}G_{t+1} + \varepsilon_{f,t+1}, \tag{IA.71}$$

with $R_{f,t+1}$ the $N_M \times 1$ return vector and Z_t the $N_M \times L$ characteristic matrix. Conditionally on $(\Gamma_{\alpha,f}, \Gamma_{\beta,f}, \Gamma_{\delta,f})$, the latent factors solve

$$F_{t+1} = \left(\Gamma_{\beta,f}^\top Z_t^\top Z_t\Gamma_{\beta,f}\right)^{-1}\Gamma_{\beta,f}^\top Z_t^\top\left(R_{f,t+1} - Z_t\Gamma_{\alpha,f} - Z_t\Gamma_{\delta,f}g_{t+1}\right), \qquad t = 1, \ldots, T-1, \tag{IA.72}$$

that is, a cross-sectional regression of returns net of characteristic-based intercepts and observable-factor exposures on dynamic IPCA betas. Conditionally on $\{F_{t+1}\}$, the coefficients $(\Gamma_{\alpha,f}, \Gamma_{\beta,f}, \Gamma_{\delta,f})$ are estimated by least squares from the stacked regression of $R_{f,t+1}$ on Z_t, Z_tF_{t+1}, and Z_tG_{t+1}. We iterate these two steps until convergence, imposing the normalization $\Gamma_{\beta,f}^\top\Gamma_{\beta,f} = I_{n_F}$ and the orthogonality restriction $\Gamma_{\delta,f}^\top\Gamma_{\beta,f} = 0_{M\times n_F}$ to separate the variation attributed to latent IPCA factors from that attributed to the pre-specified traded factors. We estimate these nested models separately for stocks and for bonds.

Table IA.I: Out-of-sample predictive results for one-month-ahead stock market returns

Predictor	$R^2_{OS,\mu}$	p-value$_\mu$	$R^2_{OS,0}$	p-value$_0$
`model`	2.96	[0.054]	2.97	[0.043]
`svix`	2.20	[0.027]	2.22	[0.092]
`sntm`	1.49	[0.010]	1.51	[0.010]
`eqty_idx`	1.34	[0.069]	1.36	[0.011]
`rdsp`	1.25	[0.033]	1.27	[0.048]
`cs10yr`	0.93	[0.012]	0.95	[0.053]
`tail`	0.92	[0.068]	0.94	[0.025]
`infl`	0.71	[0.080]	0.73	[0.059]
`disag`	0.69	[0.052]	0.71	[0.042]
`fbm`	0.28	[0.121]	0.29	[0.098]
`wtexas`	0.17	[0.241]	0.18	[0.175]
`tchi`	0.05	[0.199]	0.06	[0.088]
`tms`	−0.18	[0.233]	−0.16	[0.150]
`ndrbl`	−0.19	[0.102]	−0.17	[0.058]
`shtint`	−0.22	[0.153]	−0.20	[0.002]
`skvw`	−0.28	[0.172]	−0.26	[0.071]
`dfr`	−0.71	[0.264]	−0.69	[0.188]
`bond_idx`	−1.03	[0.232]	−1.01	[0.202]
`lzrt`	−1.45	[0.275]	−1.43	[0.036]
`ntis`	−1.61	[0.507]	−1.59	[0.257]
`vix`	−1.80	[0.394]	−1.78	[0.385]
`impvar`	−2.17	[0.524]	−2.15	[0.423]
`avgcor`	−2.21	[0.350]	−2.19	[0.224]
`e/p`	−2.34	[0.226]	−2.32	[0.054]
`rsvix`	−3.15	[0.599]	−3.13	[0.533]
`dtoat`	−3.24	[0.202]	−3.22	[0.332]
`vix_sqr`	−3.46	[0.592]	−3.45	[0.544]
`oas`	−4.28	[0.620]	−4.26	[0.498]
`dfy`	−4.77	[0.728]	−4.75	[0.593]
`d/y`	−5.16	[0.656]	−5.14	[0.346]
`ogap`	−5.20	[0.677]	−5.18	[0.302]
`dtoy`	−5.21	[0.572]	−5.19	[0.541]
`ygap`	−5.92	[0.640]	−5.90	[0.383]
`d/p`	−7.20	[0.792]	−7.18	[0.546]
`b/m`	−9.48	[0.620]	−9.46	[0.414]
`vrp`	−10.25	[0.594]	−10.23	[0.618]
`svar`	−12.87	[0.877]	−12.85	[0.802]
`d/e`	−53.59	[0.867]	−53.57	[0.849]

The table presents out-of-sample predictive results for one-month-ahead excess returns on the stock market. The columns $R^2_{OS,\mu}$ and p-value$_\mu$ report the out-of-sample R^2 and Clark and West (2007) p-values using a rolling 60-month mean as the benchmark. The columns $R^2_{OS,0}$ and p-value$_0$ report the corresponding statistics using the zero mean benchmark. Predictors are sorted by $R^2_{OS,\mu}$ from highest to lowest. All R^2_{OS} values are expressed in percentage terms. The predictor `model` refers to the model-implied expected stock return, `svix` is Martin (2017)'s SVIX, and `cs10yr` is the 10-year bond credit spread. The remaining predictors are defined in Goyal et al. (2024). For the Goyal & Welch predictors we download all predictor data from Amit Goyal's website. We limit the set of predictors to those which match our empirical data spanning 1997:01–2022:12.

Table IA.II: Out-of-sample predictive results for one-month-ahead bond market returns

Predictor	$R^2_{OS,\mu}$	p-value$_\mu$	$R^2_{OS,0}$	p-value$_0$
d/e	12.27	[0.073]	10.74	[0.087]
model	8.33	[0.048]	7.22	[0.035]
cs10yr	3.91	[0.110]	2.24	[0.121]
eqty_idx	3.61	[0.017]	1.94	[0.009]
skvw	0.76	[0.184]	−0.97	[0.382]
sntm	0.42	[0.272]	−1.31	[0.541]
infl	−0.72	[0.454]	−2.47	[0.745]
tchi	−0.88	[0.571]	−2.63	[0.744]
fbm	−0.99	[0.381]	−2.74	[0.662]
rdsp	−1.00	[0.654]	−2.75	[0.721]
wtexas	−1.07	[0.374]	−2.83	[0.525]
ygap	−1.20	[0.142]	−2.96	[0.299]
ndrbl	−1.34	[0.143]	−3.10	[0.327]
disag	−1.34	[0.429]	−3.11	[0.492]
tail	−1.76	[0.485]	−3.53	[0.445]
avgcor	−1.82	[0.253]	−3.59	[0.352]
dtoat	−2.46	[0.225]	−4.24	[0.620]
tms	−2.84	[0.356]	−4.63	[0.557]
e/p	−2.98	[0.363]	−4.77	[0.687]
impvar	−3.69	[0.717]	−5.49	[0.531]
d/y	−3.97	[0.298]	−5.77	[0.255]
b/m	−4.05	[0.343]	−5.86	[0.245]
vix	−4.21	[0.862]	−6.02	[0.781]
vix_sqr	−4.78	[0.823]	−6.61	[0.729]
rsvix	−4.90	[0.803]	−6.72	[0.716]
dfr	−5.25	[0.040]	−7.08	[0.037]
dfy	−5.35	[0.328]	−7.18	[0.489]
svix	−5.94	[0.282]	−7.78	[0.327]
lzrt	−6.24	[0.861]	−8.09	[0.711]
dtoy	−6.94	[0.812]	−8.80	[0.866]
shtint	−7.12	[0.724]	−8.98	[0.322]
ntis	−7.20	[0.905]	−9.07	[0.847]
bond_idx	−7.80	[0.191]	−9.67	[0.244]
d/p	−9.73	[0.806]	−11.63	[0.804]
oas	−9.92	[0.837]	−11.83	[0.844]
ogap	−12.96	[0.341]	−14.92	[0.200]
svar	−13.93	[0.916]	−15.91	[0.899]
vrp	−23.94	[0.837]	−26.09	[0.867]

The table presents out-of-sample predictive results for one-month-ahead excess returns on the bond market. The columns $R^2_{OS,\mu}$ and p-value$_\mu$ report the out-of-sample R^2 and Clark and West (2007) p-values using a rolling 60-month mean as the benchmark. The columns $R^2_{OS,0}$ and p-value$_0$ report the corresponding statistics using the zero mean benchmark. Predictors are sorted by $R^2_{OS,\mu}$ from highest to lowest. All R^2_{OS} values are expressed in percentage terms. The predictor `model` refers to the model-implied expected bond return, `svix` is Martin (2017)'s SVIX, and `cs10yr` is the 10-year bond credit spread. The remaining predictors are defined in Goyal et al. (2024). For the Goyal & Welch predictors we download all predictor data from Amit Goyal's website. We limit the set of predictors to those which match our empirical data spanning 1997:01–2022:12.

Table IA.III: Summary statistics by industry

Panel A: First six industries

	Business Equip.	Chemicals	Energy	Finance	Health-care	Manu-facturing
Stock excess return (%): $R_{I_S,t}$	11.23	11.02	10.49	9.95	10.71	10.15
Rep. firm stock vol. (%): $\sigma^I_{S,t}$	35.49	26.08	34.87	29.08	27.81	29.01
DH corp. bond excess return (%): $R_{I_B,t}$	2.15	1.46	2.48	1.96	1.90	1.66
Rep. firm DH corp. bond vol. (%): $\sigma^I_{B,t}$	5.21	3.74	6.25	4.65	4.13	4.27
Rep. firm corp. bond (bps): $CS^I_{10,t}$	188.93	128.51	185.08	176.89	156.64	155.55
Rep. firm leverage: Lev^I_t	0.31	0.32	0.41	0.68	0.28	0.37
Rep. firm total debt ($ bill.)	8.16	6.16	8.65	53.21	11.09	10.39
Number of firms	25.97	17.03	20.31	65.13	14.70	59.11

Panel B: Last six industries

	Shops	Telecom	Cons. Non-Dur.	Cons. Dur.	Utilities	Other
Stock excess return (%): $R_{I_S,t}$	10.01	9.32	8.74	2.29	8.95	10.86
Rep. firm stock vol. (%): $\sigma^I_{S,t}$	28.88	30.38	24.50	36.17	23.01	31.07
DH corp. bond excess return (%): $R_{I_B,t}$	1.69	2.59	1.49	−0.05	1.75	2.12
Rep. firm DH corp. bond vol. (%): $\sigma^I_{B,t}$	4.80	6.24	4.01	6.87	5.49	5.47
Rep. firm corp. bond (bps): $CS^I_{10,t}$	164.40	243.65	144.47	291.33	206.84	224.70
Rep. firm leverage: Lev^I_t	0.36	0.48	0.34	0.60	0.62	0.44
Rep. firm total debt ($ bill.)	7.30	28.54	6.77	48.22	13.05	6.81
Number of firms	31.86	11.83	24.48	6.89	26.46	34.68

The table reports summary statistics for key return and risk variables across the twelve Fama–French industry groups for both industry portfolios and the representative firm of each industry. The sample is based on S&P 500 firms with both traded equity and outstanding corporate bonds. For each industry, we report the time-series average of the following variables: stock and duration hedged (DH) bond portfolio excess returns (annualized and in percent), the conditional monthly return volatilities of the representative firm's stock and DH bond returns estimated via NGARCH models (in percent), the representative firm's 10-year credit spread (in basis points), leverage (total debt over total assets), and total debt in billions of U.S. dollars. The representative firm in each industry is constructed as the equally weighted average across individual firms within the group. The bottom row of each panel reports the average number of firms per industry per month. Bond returns are hedged using duration-matched Treasury returns. Panel A presents results for the first six industries while Panel B covers the remaining six. The sample period is 1997:01–2022:12.

Table IA.IV: Estimated parameters of industry representative firms

Panel A: First six industries

	Business Equip.	Chemicals	Energy	Finance	Health-care	Manu-facturing
Default barrier (A_D^R)	5.44	4.11	5.76	35.47	7.40	6.93
Asset beta (β_R)	1.15	1.09	1.35	0.81	0.89	1.15
Idiosyncratic volatility in % (σ_R)	2.85	1.54	3.15	0.66	3.71	1.70
Coupon in \$ (c^R)	0.13	0.10	0.26	1.35	0.17	0.18

Panel B: Last six industries

	Shops	Telecom	Cons. Non-Dur.	Cons. Dur.	Utilities	Other
Default barrier (A_D^R)	4.87	19.03	4.52	32.15	8.70	4.54
Asset beta (β_R)	0.96	0.93	1.07	0.70	0.68	0.92
Idiosyncratic volatility in % (σ_R)	1.84	1.14	1.36	0.69	0.19	1.75
Coupon in \$ (c^R)	0.11	0.45	0.11	0.87	0.22	0.11

The table reports the fixed and estimated values for the structural model parameters capturing each industry's representative firm dynamics. Panel A presents the parameters for the first six industries, and Panel B presents the parameters for the remaining ones. Industries are split based on the Fama-French Industry 12 classification. Note that parameters describing the dynamics of systematic risks are taken as given from the market-level estimation, including the prices of risks (i.e., $\{\kappa, \theta, \delta, \rho, \xi_{M\perp V}, \xi_V\}$), which leaves us with four free parameters to be estimated for each industry (A_D^R, β_R, σ_R, and c^R). The default barrier is fixed to 2/3 of the industry average of total debt, expressed in \$ Billion, and the remaining parameters are obtained via maximum likelihood estimation. For each industry, we filter out $\hat{A}_t^R$ each month from the industry 10-year credit spread, $CS_{10,t}^I$, and set $\hat{V}_t$ from the filtered value obtained from the market-level estimation. The sample period is 1997:01–2022:12, and the data observation frequency is monthly.

Table IA.V: Benchmark in-sample predictive performance for industry portfolio returns

	Panel A: Stocks					Panel B: DH Corp. bonds				
	$\gamma_0^{Bench.}$	$\gamma_1^{Bench.}$	$R^2_{Adj.}$	R^2_{Theory}	$\alpha_0^{Bench.}$	$\gamma_0^{Bench.}$	$\gamma_1^{Bench.}$	$R^2_{Adj.}$	R^2_{Theory}	$\alpha_0^{Bench.}$
Business Equipment	0.00	2.25	1.02	0.78	0.06	−0.04	3.19	3.03	2.06	0.00
	(−0.04)	(1.20)			(1.26)	(−1.08)	(1.33)			(0.22)
Chemicals	0.05	1.24	0.41	0.16	0.06	−0.05	5.10	3.83	1.76	0.00
	(0.64)	(0.67)			(1.73)	(−1.54)	(1.78)			(0.24)
Energy	−0.04	2.84	1.12	0.89	0.05	−0.14	8.89	8.08	2.05	0.01
	(−0.32)	(1.11)			(0.98)	(−2.06)	(2.29)			(0.43)
Finance	0.07	0.58	−0.21	−0.02	0.05	−0.05	3.66	5.18	2.89	0.00
	(0.86)	(0.28)			(1.03)	(−1.03)	(1.20)			(0.15)
Health Care	0.06	0.95	0.27	−0.07	0.05	−0.07	5.44	5.23	2.10	0.00
	(1.16)	(0.96)			(1.75)	(−2.03)	(2.38)			(0.46)
Manufacturing	0.06	0.81	−0.05	0.04	0.05	−0.04	3.63	2.24	1.52	0.00
	(0.89)	(0.48)			(1.19)	(−0.86)	(1.07)			(0.13)
Shops	0.04	1.19	0.47	0.36	0.05	−0.04	3.65	1.99	1.41	0.00
	(0.70)	(0.86)			(1.47)	(−0.87)	(1.05)			(0.05)
Telecom-munications	−0.03	2.47	1.96	1.43	0.04	−0.09	4.70	4.50	2.14	0.00
	(−0.49)	(1.77)			(0.99)	(−1.89)	(2.05)			(0.11)
Consumer Non-Durables	0.07	0.27	−0.27	−0.62	0.04	−0.03	3.43	2.15	1.54	0.00
	(1.62)	(0.24)			(1.24)	(−0.95)	(1.17)			(0.06)
Consumer Durables	−0.04	1.19	−0.09	0.49	−0.03	0.04	−1.43	1.77	−4.50	−0.03
	(−0.35)	(0.46)			(−0.46)	(1.15)	(−0.78)			(−1.13)
Utilities	0.10	−0.15	−0.31	−0.88	0.04	−0.07	4.17	4.92	2.50	0.00
	(2.62)	(−0.20)			(1.15)	(−2.27)	(2.27)			(−0.24)
Other	0.05	1.23	0.28	0.23	0.06	−0.06	3.51	3.41	2.13	0.00
	(0.67)	(0.71)			(1.41)	(−1.10)	(1.29)			(−0.09)
Average	0.03	1.24	0.38	0.23	0.04	−0.05	3.99	3.86	1.47	0.00

The table reports predictive regression results for one-month-ahead excess returns on the stock and duration hedged (DH) corporate bond industry portfolios. Panel A uses the squared-VIX index ($SVIX_t$) for industry stock portfolios as predictors, while Panel B reports results when using the 10-year industry-average credit spread ($CS^I_{10,t}$) for DH corporate bond portfolios. Reported statistics include the annualized intercept ($\gamma_0^{Bench.}$) and slope ($\gamma_1^{Bench.}$) coefficients in the first row for each industry, with Newey–West t-statistics reported in parentheses below. $\alpha_0^{Bench.}$ denotes the benchmark's annualized pricing error, defined as the difference between the next month return and the benchmark's conditional forecast. The Newey–West t-statistics test the null hypothesis that the corresponding coefficient equals zero. Model fit is summarized by the adjusted $R^2_{Adj.}$ (%) and by R^2_{Theory} (%), defined as the adjusted R^2 from a predictive regression imposing a zero intercept and a unit slope. The last row of the table reports the average parameters and R-squared. The sample period is 1997:01–2022:12.

Table IA.VI: In-sample predictive regression results for one-month-ahead returns (LIQ Sample)

	Model	HKM	FF5	LIQ	IPCA			
					n_F=2	n_F=3	n_F=5	n_F=10
Panel A: Stocks								
γ_0	0.00	0.00	0.00	0.00	−0.00	−0.00	−0.00	0.00
t-stat$_{\{H_0:\gamma_0=0\}}$	(0.98)	(0.23)	(0.21)	(0.35)	(−0.18)	(−0.30)	(−0.06)	(0.49)
γ_1	0.72	0.98	0.99	0.97	1.10	1.15	1.01	0.66
t-stat$_{\{H_0:\gamma_1=0\}}$	(1.24)	(3.23)	(3.28)	(3.58)	(3.90)	(3.80)	(3.22)	(2.06)
t-stat$_{\{H_0:\gamma_1=1\}}$	(−0.49)	(−0.07)	(−0.02)	(−0.13)	(0.35)	(0.49)	(0.03)	(−1.06)
$\mathcal{W}$ p-value	[0.58]	[0.97]	[0.97]	[0.94]	[0.94]	[0.88]	[1.00]	[0.35]
R^2_{Adj} (%)	0.47	0.19	0.18	0.22	0.11	0.11	0.08	0.05
R^2_{Theory} (%)	0.33	0.18	0.17	0.22	0.11	0.10	0.08	0.02
R^2_{Pred} (%)	1.54	1.39	1.38	1.42	1.32	1.31	1.28	1.23
Panel B: Corporate Bonds								
γ_0	−0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
t-stat$_{\{H_0:\gamma_0=0\}}$	(−2.02)	(0.49)	(0.57)	(0.66)	(0.61)	(0.55)	(0.60)	(0.11)
γ_1	1.87	0.88	0.86	0.85	0.75	0.74	0.77	0.72
t-stat$_{\{H_0:\gamma_1=0\}}$	(3.74)	(3.21)	(3.33)	(3.16)	(3.46)	(3.55)	(3.25)	(3.53)
t-stat$_{\{H_0:\gamma_1=1\}}$	(1.74)	(−0.42)	(−0.55)	(−0.54)	(−1.18)	(−1.23)	(−0.96)	(−1.36)
$\mathcal{W}$ p-value	[0.11]	[0.66]	[0.56]	[0.40]	[0.12]	[0.15]	[0.24]	[0.33]
R^2_{Adj} (%)	3.85	0.52	0.49	0.51	0.43	0.41	0.42	0.29
R^2_{Theory} (%)	2.98	0.51	0.47	0.49	0.38	0.35	0.38	0.17
R^2_{Pred} (%)	3.59	1.14	1.10	1.12	1.01	0.98	1.01	0.81

The table presents in-sample predictive results for one-month-ahead excess stock returns and duration-adjusted (DH) corporate bond returns including the traded Pastor and Stambaugh (2003) stock and bond liquidity factors over a shorter sample period: 2003:08–2022:12. Panel A (B) reports the results for Stocks (Corporate Bonds). The column labeled 'Model' corresponds to the model-implied conditional risk premia as predictors. The columns n_F = 2, 3, 5, and 10 are the models estimated via IPCA with differing number of latent factors. The factors are instrumented with the Kelly et al. (2023) 29 stock and bond characteristics and a constant. The 'HKM' column is the He et al. (2017) two-factor model, which includes the stock market and traded intermediary capital factor. The 'FF5' column is the original Fama and French (1993) five-factor model, which includes the Fama-French three-factors and the DEF and $TERM$ factors. The 'LIQ' column is the two-factor liquidity model with the Pastor and Stambaugh (2003) stock and bond traded liquidity factors. These models are also estimated via the IPCA methodology as pre-specified, observable factors, instrumented with the same 29 characteristics and a constant. The IPCA conditional expected return forecasts are defined as, $\lambda^{\text{IPCA}}_{f,j,t+1} \equiv z'_{j,t}\left(\widehat{\Gamma}_{\alpha,f} + \widehat{\Gamma}_{\beta,f}\,\widehat{\mu}_f\right)$, where the Γs are estimated via IPCA, $z_{j,t}$ are the characteristics and $\widehat{\mu}_f$ are the time-series averages of the traded factors (their risk premiums). The γ_0 and γ_1 coefficients are the constant and slope coefficients from regressions of the realized stock or bond returns on the predicted expected return values from the estimated models. R^2_{Adj} is the R-squared from this regression, R^2_{Pred} and R^2_{Theory} are defined as: $R^2_{Pred} = 1 - \sum_{j,t}\left(R_{f,j,t+1} - (\gamma_0 + \gamma_1 \lambda_{f,j,t})\right)^2 / \sum_{j,t} R^2_{f,j,t+1}$, and $R^2_{Theory} = 1 - \left[\sum_{i,t}\left(R_{f,j,t+1} - \lambda_{f,j,t}\right)^2 /(N-k)\right] / \left[\sum_{j,t}\left(R_{f,j,t+1} - \bar{R}\right)^2 /(N-1)\right]$, respectively. The sample period is 2003:08–2022:12.

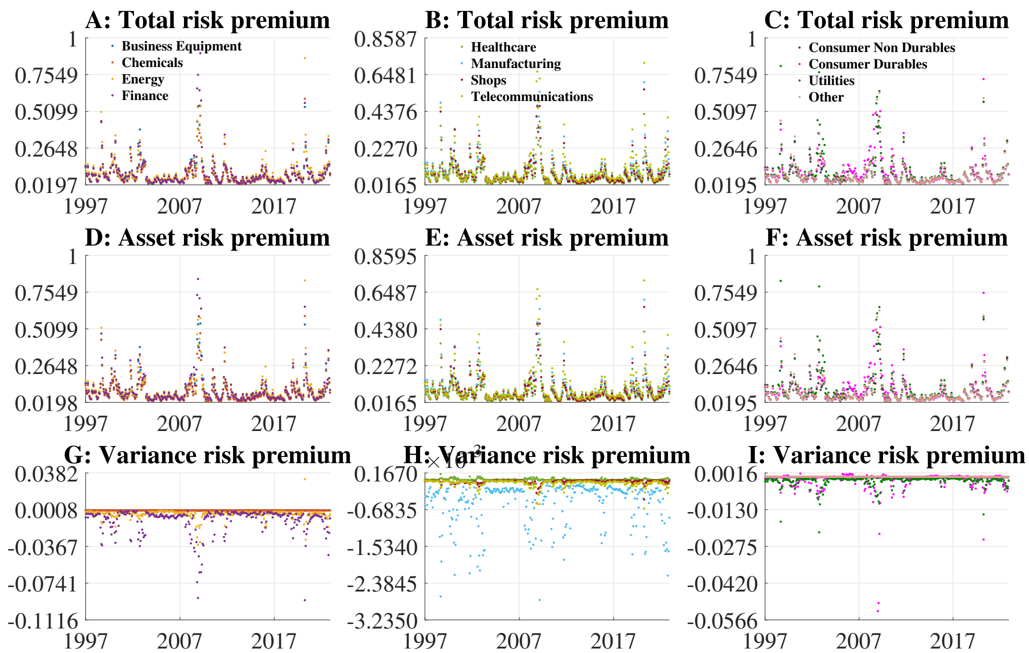

Figure IA.1: Decomposition of risk premia in industry stock portfolios.

The figure shows the time-series of the conditional total risk premium (Panels A to C) and its decomposition into asset and variance risk premia for industry stock portfolios. Panels D to F present the asset risk premium components, while Panels G to L display the conditional variance risk premia. Industries are divided into three groups and are identified by distinct colors, as indicated in the legend in Panels A to C. Panels in a given vertical column present the results for the same industry group. The sample period is 1997:01–2022:12.

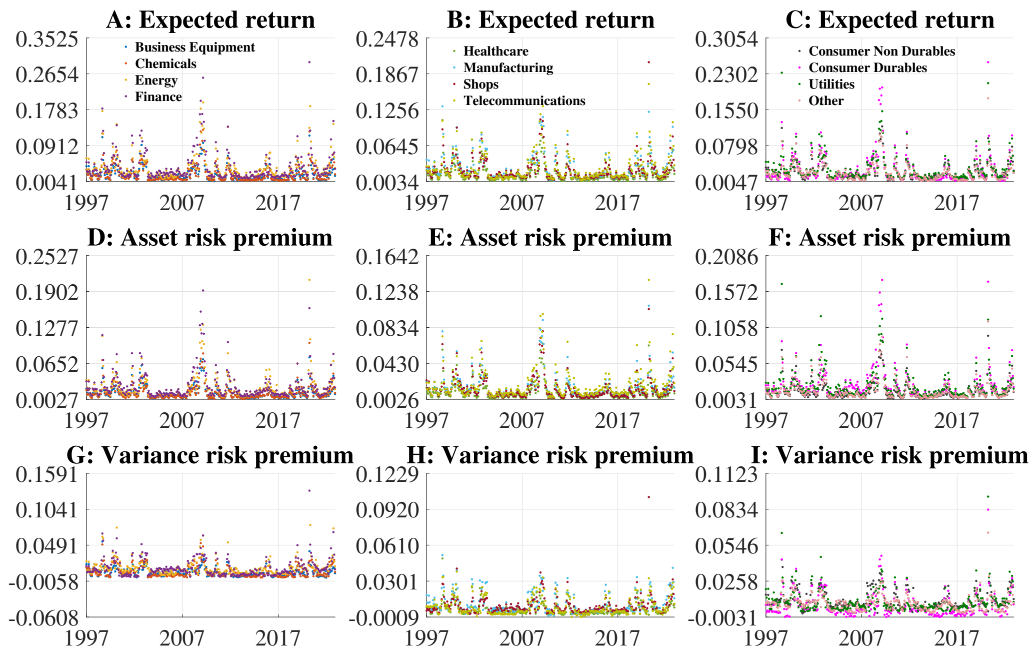

Figure IA.2: Decomposition of risk premia in industry DH bond portfolios.
The figure plots the time series of the conditional total risk premium (Panels A to C) and its decomposition into asset and variance risk premia for industry duration hedged (DH) bond portfolios. Panels D to F present the asset risk premium components, while Panels G to L display the conditional variance risk premia. Industries are divided into three groups and are identified by distinct colors, as indicated in the legend in Panels A to C. Panels in a given vertical column present the results for the same industry group. The sample period is 1997:01–2022:12.