

Model-Based Cross-Section Factors in Corporate Bonds

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Abstract

Using a structural default model with stochastic interest rates and liquidity shocks, we identify three fundamental sources of fixed-income risk – duration, credit, and liquidity – from cross-section corporate bond returns. Our estimation is unique in that the three latent factors are extracted from the model-implied factor loadings, offering a clean identification of the risk of duration, credit, and liquidity and how they interact during market stress. Our model-based factors provide a unified framework to answer questions of current importance: the rapidly increasing long-term interest rate, its impact on the credit and liquidity factors, and the safety of U.S. Treasuries.

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1 Introduction

Since 2008, the U.S. fixed-income market has experienced significant shocks in its three fundamental sources of risk – duration, credit, and liquidity. For policy makers, as well as investors, differentiating these risk factors is a task of central importance – the same observed movement in asset prices may reflect deteriorating fundamental risks, impaired market liquidity, or uncertainty in long-term interest rates, or some combination of the three. A clean identification of the risk factors can therefore help differentiate the economic driver of the crises, clarify how different risks interact during market stress, and evaluate the relevant policy responses.

In this paper, we focus on the U.S. corporate bond market for this exact purpose. With an amount outstanding of \$11.55 trillion by 2025, the U.S. corporate bond market is the most important debt financing channel for large U.S. corporations and an essential investment vehicle for global financial institutions and investors. Sitting at the intersection of finance, macro, and intermediation, it also contains rich information on duration, credit, and liquidity risks. As a fixed-income asset, its pricing is linked directly to the time-varying interest rates; as a defaultable security, it reflects the overall health and survival of Corporate America; and as a predominantly dealer-intermediated security, its liquidity condition reflects the balance-sheet capacity of financial institutions.

In addition to its considerable size, the U.S. corporate bond market also offers a large cross-section of bonds with varying degrees of credit quality, maturity, and liquidity. Focusing on this rich and vast cross-section of corporate bond returns, our main objective in this paper is to extract the common risk factors of duration, credit, and liquidity from it. Central to our empirical approach is a structural model of default with stochastic interest-rate risk and a systematic liquidity factor. Associated with the three shocks in the model are three risk factors – duration, credit, and liquidity. Unlike the existing cross-sectional literature, which uses stock or bond characteristics to form empirically motivated factors, our empirical approach is disciplined and informed by the structural model – our risk factors are extracted using model-implied factor loadings. As such, our empirical approach offers a clean identification of the three fundamental sources of risk in fixed-income markets.

Over the past two decades, the corporate bond market has been at the forefront of the crises experienced by the broader fixed-income market. Against this backdrop, our model-based factors can be used to gauge and differentiate the relative importance of credit, liquidity, and duration.¹ In particular, the extreme outcomes of our model-based factors

¹For example, by separately identifying the credit and liquidity risk factors, we can disentangle liquidity from credit – an issue of great importance during the 2008 financial crisis. Examining the interactions of

can help identify episodes of historical importance – dash-for-cash when our duration factor suddenly drops, flight-to-quality when our credit factor experiences large drawdowns, and flight-to-liquidity with extreme realizations of our liquidity factor.

More broadly, the model-based factors provide a unified framework for studying several questions of current importance: the forces behind the rapidly increasing long-term interest rates, their economic consequences, and the safety of U.S. Treasuries. Using the duration factor, we can extract the safety premium from U.S. Treasuries, differentiating flight-to-safety from dash-for-cash. Decomposing credit spreads into credit and liquidity components, we can identify whether the negative correlation between credit spreads and interest rates originates from credit or liquidity risks. Finally, examining the lead/lag relation among the three factors, we can get a better understanding of how rising long-term interest rate affects credit and liquidity, and how credit deterioration can lead to worsening liquidity risk.

Model-Based Extraction of Common Risk Factors – Different from the equity market, the corporate bond market enjoys a close connection between market pricing and the fundamental risk factors, as captured by the long line of structural models of default pioneered by [Merton \(1974\)](#). In our model, assuming the existence of a risk-neutral measure and letting P_t^i be the time- t price of asset i ,

$$\frac{dP_t^i}{P_t^i} - r_t dt = b_i dF_t^Q + dB_t^i, \quad i = 1, 2, \dots, N, \quad (1)$$

where the latent risk factor, dF_t^Q , is zero mean under the risk-neutral measure Q and non-zero under the physical measure, with the factor risk premium λ_t driving the difference:

$$dF_t^Q = \lambda_t dt + dF_t. \quad (2)$$

Representing unpriced idiosyncratic risk, dB_t^i is zero mean under both measures. Given the time- t market-observed returns across i and their respective model-implied factor loadings b_i , we can back out the time- t risk factors dF_t^Q .

Central to our factor extraction are the model-implied factor loading b_i , which we derive from structural models of default. Taking the classic default model of [Merton \(1974\)](#) as an example, the time- t bond value is $P_t = Ke^{-r\tau}N(d_2) + V_tN(-d_1)$, where $\tau = T - t$ and V_t is the time- t value of assets. The corresponding model-implied loading on asset value is therefore $b_i^V = \frac{\partial \ln P_t}{\partial \ln V_t}$. We further generalize this framework by introducing stochastic interest

the risk factors, we can further identify trends of comovement between liquidity and credit and analyze the impact of duration risk on credit and liquidity risks – an issue of timely relevance amidst the recent sharp increase of long-term interest rates.

rate and a systematic liquidity factor. Overall, our three-factor model of credit, duration, and liquidity is estimated using the corresponding factor loadings – the model-implied factor loading for the credit risk, b_i^V , is closely associated with the distance-to-default measure; the factor loading for the interest-rate risk r_t can be derived by $b_i^r = \frac{\partial \ln P_t}{\partial r_t}$, which is essentially the duration of the bond. We further add a liquidity risk factor, proxying each bond’s systematic liquidity exposure with the measure in [Bao, Pan, and Wang \(2011\)](#).

Leveraging the large cross-section of bond returns, we extract the time- t latent factors using the model-based factor loadings. Specifically, we run the cross-sectional regression of excess bond returns on their respective factor loadings to obtain the time- t slope coefficients, which, according to equation (1), are in fact the time- t latent risk factors of credit, duration, and liquidity. Stacking the time- t latent factors over time, we obtain the time-series of credit, duration, and liquidity factors.²

The Economic Content of the Model-Based Factors – Both the credit and liquidity risk factors are significantly priced. From August 2002 through March 2025, the credit factor carries a risk premium of 29.8 bps per month with a t -statistic of 3.36, while the liquidity factor carries a premium of 5.4 bps with a t -statistic of 4.64. The average return of the duration factor is 1.2 bps per month, but is statistically insignificant.

To further validate the economic content of our model-based factors, we first use the extreme outcomes of our factors to locate the historically important episodes of dash-for-cash, flight-to-quality, and flight-to-liquidity. Prominent examples of dash-for-cash identified by our duration factor include: June 20, 2013, the day after Bernanke’s taper speech; March 10, 17, and 18, 2020, events of dash-for-cash amid Covid-19; and June 13, 2022, when the CPI announcement for May indicates accelerating inflation. Episodes of flight-to-quality captured by our credit factor include September 15, 2008 (Lehman bankruptcy), March 12, 2020 (Covid-19), and March 13, 2023 (SVB banking stress). Flight-to-liquidity days captured by our liquidity factor include May 6, 2010 (flash crash and liquidity withdrawal), March 23, 2020 (QE infinite and Fed SMCCF to provide liquidity to corporate bonds), and March 17, 2023 (FRB banking stress and large banks’ exposure).

Second, we examine the direct links between the factors and the markets in which the underlying risks are present. Consistent with its model-implied interest-rate exposure, the

²While this empirical approach of running cross-sectional regression to extract the latent factors is similar to that of [Kelly, Pruitt, and Su \(2019\)](#), [Fama and French \(2020\)](#) and [Chen et al. \(2026\)](#), there is an important and conceptual difference between our approach and these studies. In particular, instead of using characteristics, we use model-implied factor loadings to extract the latent factors and, more importantly, the pricing relation in equation (1) is dictated by an arbitrage-free asset pricing model. This model-based factor approach distinguishes our paper from existing studies of the corporate-bond cross-section that use empirically motivated factors (e.g., [Fama and French \(1993\)](#) and [Dickerson, Mueller, and Robotti \(2023\)](#)).

duration factor is strongly negatively related to changes in the 10-year Treasury yield after controlling for changes in the three-month Treasury bill rate. Recent work by [van Binsbergen, Nozawa, and Schwert \(2025\)](#) and [Cui, Lu, and Song \(2026\)](#) emphasizes duration as a central component of corporate-bond returns, isolating Treasury exposure bond by bond with duration- or cash-flow-matched benchmarks. We instead estimate the duration factor jointly with credit and liquidity using model-implied loadings across the corporate-bond cross-section. Over the common sample, our duration factor correlates 0.72 with the duration-matched Treasury component of [van Binsbergen, Nozawa, and Schwert \(2025\)](#), while our credit factor correlates 0.69 with their duration-adjusted corporate-bond component. Turning to intermediary capacity, liquidity-factor volatility is higher when primary dealers hold smaller net positions in investment-grade and high-yield corporate bonds, a pattern that connects liquidity risk to dealers’ capacity to warehouse it.

Third, we examine the macro drivers of our model-based bond factors, and find that the credit factor responds most strongly to the VIX index, the liquidity factor moves most closely with financial uncertainty, and the duration factor is most tightly linked to the MOVE index, which is the VIX for the bond market.

Empirical Performance of the Model-Based Factors – Our model-based risk factors can explain the risk premiums across a broad set of risky asset classes, including the U.S. equity market, U.S. and foreign corporate bonds, and emerging-market sovereign bonds. Credit explains an important share of these returns, while duration and liquidity provide complementary explanatory power. Within the corporate-bond market, our model-based factors can explain almost all of the cross-section portfolios, except for the portfolio containing the highest-rated corporate bonds, which earn an extra average return relative to the three-factor model. Similar to the credit spread puzzle of [Huang and Huang \(2012\)](#), the main limitation of the structural model of default is the Gaussian mapping between the distance-to-default and the risk-neutral probability of default. In particular, the model understates the probability of rare, correlated defaults among highly rated issuers. As a result, the corresponding model-implied loadings on the credit factor are close to zero for such highly rated bonds, making them as safe as the riskfree bonds. While the model does pick up the liquidity exposures for such bonds, the liquidity risk premium can substantially attenuate, but does not eliminate this extra alpha.

Our model-based factors also provide a diagnostic tool for identifying the economic drivers of characteristic-sorted portfolio returns. We examine portfolios sorted on yield spread, duration, and bond volatility, which [Kelly, Palhares, and Pruitt \(2023\)](#) identify as especially informative. Our model-based factor loadings of these empirically motivated portfolios reveal that the portfolios sorted by yield-spread and bond-volatility have increasing

credit and liquidity exposures, while the duration-sorted portfolios have increasing duration exposure. Moreover, our three-factor model explains the return patterns across all three portfolio families – the corresponding three-factor alphas of the sorted portfolios become insignificant, both economically and statistically.

Applications of the Model-Based Factors – First, taking advantage of our duration factor, we decompose U.S. Treasury returns into a pure duration component and a Treasury-specific safety component. Using the same model-based approach, we extract a Treasury duration factor from cross-section Treasury bonds. Because Treasury duration combines the common interest-rate component captured by corporate duration with the return benefit specific to Treasury safety, we define the Safety Premium as Treasury duration minus corporate duration. This return-based decomposition complements the safe-asset-demand measures of [Jiang, Krishnamurthy, and Lustig \(2021, 2023\)](#) by distinguishing compensation for a common duration shock from Treasury-specific safety value. We show that March 2020 is the only episode in which Treasuries lose both duration and safety value simultaneously, consistent with broad liquidation during the dash-for-cash.

Second, we decompose corporate credit spreads into credit and liquidity components and relate each component to the common long-term interest-rate factor. We find a positive correlation of 0.39 between the credit and duration factors, indicating that increases in long-term interest rates are associated with deteriorating credit conditions. In contrast, the liquidity and duration factors have a correlation of -0.26 , indicating that declines in long-term rates are associated with deteriorating corporate-bond liquidity. Consistent with the liquidity component being an important driver of credit spreads, [Li \(2026\)](#) shows that higher long-term rates strengthen life insurers’ balance sheets, increase corporate-bond demand, and lower credit spreads. In the standard structural model of default with stochastic interest rates by [Longstaff and Schwartz \(1995\)](#), which does not include liquidity, the negative spread–rate relation arises through an asset-drift channel: higher interest rates raise the risk-neutral drift of firm value and thereby reduce default probabilities. Our result therefore calls for structural models of default with stochastic interest rates to also incorporate a liquidity component.

Third, we study how interest-rate conditions propagate to subsequent credit and liquidity risks, a question made especially salient by the post-COVID inflation surge and recent sharp increase in long-term U.S. Treasury yields. We find that lower duration returns (i.e., rising long-term interest rates) predict deteriorating credit conditions for high-yield bonds and worsening liquidity conditions for investment-grade bonds. The transmission therefore operates through different margins across credit quality: credit risk for high-yield issuers and market liquidity for investment-grade bonds. These results show that rising long-term rates affect corporate bonds beyond the contemporaneous duration loss, with the subsequent

credit effect concentrated among issuers most exposed to default risk.

Fourth, we examine the dynamic relation between credit and liquidity risks. Contemporaneously, the two factors are positively correlated, especially during crisis periods, and the correlation eases as the economy recovers. This pattern is consistent with the structural models of [He and Xiong \(2012\)](#), [He and Milbradt \(2014\)](#), and [Chen et al. \(2018\)](#), which incorporate both credit-driven liquidity and liquidity-driven credit. Because the contemporaneous relation cannot identify the direction of causality, we examine lead-lag relations. Including investment-grade and high-yield credit jointly, we find that both factors contain incremental information about future aggregate liquidity and together explain 14% of next month’s liquidity factor return. The investment-grade response builds gradually and remains positive over longer horizons, whereas the high-yield response is concentrated within the first several months and subsequently reverses. We find no corresponding evidence that liquidity predicts subsequent credit, identifying credit-driven liquidity as the dominant predictive direction in our sample.

Comparison with Existing Factor Models – We further compare our three-factor model with eight prominent traded and statistical specifications using common corporate bond test assets. The traded benchmarks include the corporate bond CAPM and its term-factor extension from [Dickerson, Julliard, and Mueller \(2023\)](#), the five stock-and-bond factors of [Fama and French \(1993\)](#), and the traded intermediary-capital model of [He, Kelly, and Manela \(2017\)](#). We also consider the corrected version of the four-factor model originally developed by [Bai, Bali, and Wen \(2019\)](#), using the factor series of [Dickerson, Mueller, and Robotti \(2023\)](#), and the corporate-bond duration model of [van Binsbergen, Nozawa, and Schwert \(2025\)](#). The statistical benchmarks are the corporate bond IPCA model of [Kelly, Palhares, and Pruitt \(2023\)](#) and the Regressed-PCA model of [Chen et al. \(2026\)](#).

On 50 corporate bond portfolios, our model produces a GRS p -value of 0.052, a mean absolute alpha of 8.6 bps, and an OLS cross-sectional R^2 of 0.916. [Dickerson, Mueller, and Robotti \(2023\)](#) produces the smallest mean absolute alpha, while the Regressed-PCA model attains the highest cross-sectional fit. Across 10,000 common random selections of 20 portfolios from a broader universe of 108 corporate bond strategies, our model has the lowest GRS rejection frequency and the highest mean GRS p -value. Our model also produces a higher annualized maximum Sharpe ratio than each low-dimensional traded benchmark over their matched samples. Two-way spanning tests locate the source of this performance: market, default, term, and duration factors absorb substantial variation in our credit and duration factors, whereas the liquidity factor retains a positive and significant alpha.

Related Literature – Our paper contributes to the literature on structural models of default, a field developed by the seminal work of [Merton \(1974\)](#), followed by important con-

tributions from [Black and Cox \(1976\)](#), [Leland \(1994\)](#), [Longstaff and Schwartz \(1995\)](#), [Leland and Toft \(1996\)](#), [He and Xiong \(2012\)](#) and many others. These models have been pivotal in understanding the dynamics of credit risk and its connection with either interest-rate risk or liquidity risk, but these two connections have typically been studied separately. Moreover, the existing literature has primarily focused on the models’ implications for the credit spread puzzle, including [Huang and Huang \(2012\)](#), [Chen, Collin-Dufresne, and Goldstein \(2008\)](#), [Almeida and Philippon \(2007\)](#), [Bhamra, Kuehn, and Strebulaev \(2009\)](#), [Chen \(2010\)](#), and [Huang, Nozawa, and Shi \(2025\)](#). However, the implications of structural models on bond returns have been less explored, highlighting a gap that our research aims to address. Our study develops a unified model of credit, interest-rate, and liquidity risks and evaluates its empirical performance on cross-section bond returns, extending the return implications of this classical literature.

Our paper is also related to the growing literature on identifying a common corporate bond factor structure. [Fama and French \(1993\)](#) identify the term and default factors. For the four-factor model of [Bai, Bali, and Wen \(2019\)](#), we use the corrected factor series provided by [Dickerson, Mueller, and Robotti \(2023\)](#) as the DMR4 benchmark. More recent work uses duration-based or statistical methods. [van Binsbergen, Nozawa, and Schwert \(2025\)](#) separate a duration-matched Treasury component from the duration-adjusted return on the corresponding risky market. Our approach instead retains conventional excess returns and uses model-implied cross-section loadings to estimate duration jointly with credit and liquidity. [Kelly, Palhares, and Pruitt \(2023\)](#) use instrumented principal components analysis to construct a conditional factor model for corporate bond returns, while [Chen et al. \(2026\)](#) use Regressed-PCA to study common risk factors across stocks, bonds, and options.³ In contrast, our model-based approach provides a theoretical foundation for some factors identified by statistical methods, while the economic content of the extracted factors offers diagnostic tools and applications for established findings in the literature.

Finally, our paper contributes to the literature on the safety premium or convenience yield of U.S. Treasuries. [Jiang, Krishnamurthy, and Lustig \(2021, 2023\)](#) construct a Treasury basis from currency-hedged sovereign yield differentials.⁴ As an alternative to their Treasury basis, we extract a measure of Treasury safety directly from the return differential between Treasury and corporate duration factors, which helps mitigate potential clientele effects

³Other related work includes [Dickerson, Julliard, and Mueller \(2023\)](#), [Dick-Nielsen et al. \(2024\)](#), [Elkamhi, Jo, and Nozawa \(2024\)](#), [Dang, Hollstein, and Prokopczuk \(2023\)](#), and [Bekaert, Santis, and Mondino \(2024\)](#), [Cui, Lu, and Song \(2026\)](#).

⁴Other related work on Treasury convenience yields and safe-asset demand includes [Krishnamurthy and Vissing-Jorgensen \(2012\)](#), [Du, Im, and Schreger \(2018\)](#), [Liao \(2020\)](#), and [Jiang et al. \(2024\)](#).

across sovereign markets. Our safety measure comoves positively with the Treasury basis. More importantly, our return decomposition separates pure duration risk from Treasury safety and thereby distinguishes dash-for-cash, flight-to-safety, and flight-away-from-safety.

The rest of our paper is organized as follows. Section 2 presents a structural model of default with stochastic interest rates and systematic liquidity risk. Section 3 describes the data, constructs the model-based factors, and validates their economic content. Section 4 evaluates the framework in aggregate markets and cross-sectional portfolios. Section 5 develops the four economic applications. Section 6 compares the model with existing traded and statistical factor models, and Section 7 concludes. The Appendix provides further details.

2 The Model

We extend the structural-default framework of Merton (1974) and Longstaff and Schwartz (1995) by introducing systematic liquidity risk. The model contains three systematic shocks: a common shock to firms' asset values, an interest-rate shock, and a market-wide liquidity shock. We derive the corresponding bond-level exposures in closed form and use these predetermined loadings to extract credit, duration, and liquidity factor returns from the cross-section of corporate bonds.

2.1 Default, Interest-Rate, and Liquidity Risks

Under the risk-neutral measure Q , firm i 's asset value follows

$$\frac{dV_t^i}{V_t^i} = r_t dt + \beta_i \sigma_V dB_t^V + \sigma_i dB_t^{V,i}, \quad (3)$$

where dB_t^V is the systematic shock that drives common credit conditions, β_i is firm i 's exposure to that shock, and $dB_t^{V,i}$ is a firm-specific shock. The latter is independent across firms and orthogonal to all systematic shocks. For pricing purposes, the total volatility of firm i 's asset value is

$$\sigma = \sqrt{\beta_i^2 \sigma_V^2 + \sigma_i^2}. \quad (4)$$

Following Longstaff and Schwartz (1995), the short rate obeys the Vasicek process

$$dr_t = (\alpha_r - \kappa_r r_t) dt + \eta_r dB_t^r. \quad (5)$$

Market-wide liquidity conditions are summarized by ξ_t , which follows

$$d\xi_t = (\alpha_\xi - \kappa_\xi \xi_t) dt + \eta_\xi dB_t^\xi. \quad (6)$$

Thus, ξ_t mean reverts at speed κ_ξ around $\bar{\xi} = \alpha_\xi / \kappa_\xi$. The three systematic Brownian motions $(dB_t^V, dB_t^r, dB_t^\xi)$ have pairwise correlations ρ_{Vr} , $\rho_{V\xi}$, and $\rho_{r\xi}$.

To motivate how liquidity enters prices, suppose a liquidity event arrives over $[t, t + dt]$ with conditional probability $\xi_t dt$ and reduces the market value of bond i from P_{t-}^i to $(1 - l_i)P_{t-}^i$, where $0 \leq l_i \leq 1$ is its loss-given-liquidation.⁵ The expected proportional loss over the interval is therefore $l_i \xi_t dt$. As under the recovery-of-market-value convention of [Duffie and Singleton \(1999\)](#), this expected loss rate enters the discount rate, so cash flows of bond i are discounted at $r_t + l_i \xi_t$. We use the Poisson description to motivate the product $l_i \xi_t$; for tractability, equation (6) represents the systematic expected-liquidity-cost state by a Gaussian mean-reverting process rather than tracking individual transaction arrivals. Economically, l_i captures cross-sectional differences in bond illiquidity, whereas ξ_t captures common variation in market-wide liquidity conditions.

Let $\tau = T - t$ denote time to maturity and K the default boundary. Under the Merton maturity-default convention, the bondholder receives $\min(V_T^i, K)$ at T . The bond price is therefore

$$P_t^i = \mathbb{E}_t^Q \left[\exp \left(- \int_t^T (r_s + l_i \xi_s) ds \right) \min(V_T^i, K) \right]. \quad (7)$$

By no arbitrage, a claim $H(V^i, r, \xi, t)$ satisfies

$$\begin{aligned} \frac{\sigma^2}{2} (V^i)^2 H_{VV} + \frac{\eta_r^2}{2} H_{rr} + \frac{\eta_\xi^2}{2} H_{\xi\xi} + \beta_i \sigma_V \eta_r \rho_{Vr} V^i H_{Vr} + \beta_i \sigma_V \eta_\xi \rho_{V\xi} V^i H_{V\xi} + \rho_{r\xi} \eta_r \eta_\xi H_{r\xi} \\ + r V^i H_V + (\alpha_r - \kappa_r r) H_r + (\alpha_\xi - \kappa_\xi \xi) H_\xi - (r + l_i \xi) H + H_t = 0. \end{aligned} \quad (8)$$

2.2 Risky Bond Price

Because r_t and ξ_t are Gaussian and $\ln V_T^i$ is conditionally Gaussian, both the liquidity-adjusted discount factor and the risky-bond price admit closed forms.

Lemma 1 *The price of a default-free claim paying one unit at T , discounted at $r_t + l_i \xi_t$, is*

⁵A Gaussian Ornstein–Uhlenbeck state can take negative values and therefore is not, strictly speaking, a nonnegative Poisson intensity. The arrival interpretation is used only to motivate the reduced-form product $l_i \xi_t$.

exponential affine:

$$R(r_t, \xi_t, \tau) = \mathbb{E}_t^Q \left[e^{-\int_t^T (r_s + l_i \xi_s) ds} \right] = \exp(A_i(\tau) + B(\tau)r_t + C_i(\tau)\xi_t), \quad (9)$$

where

$$B(\tau) = -\frac{1 - e^{-\kappa_r \tau}}{\kappa_r}, \quad C_i(\tau) = -l_i \frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi}, \quad (10)$$

and

$$A_i(\tau) = -\frac{\alpha_r}{\kappa_r} [\tau + B(\tau)] - \frac{\alpha_\xi}{\kappa_\xi} [l_i \tau + C_i(\tau)] + \frac{1}{2} (\omega_{rr} + l_i^2 \omega_{\xi\xi} + 2l_i \omega_{r\xi}). \quad (11)$$

The conditional integrated variances and covariance are

$$\begin{aligned} \omega_{rr}(\tau) &= \frac{\eta_r^2}{\kappa_r^2} \left[\tau + 2B(\tau) + \frac{1 - e^{-2\kappa_r \tau}}{2\kappa_r} \right], \\ \omega_{\xi\xi}(\tau) &= \frac{\eta_\xi^2}{\kappa_\xi^2} \left[\tau - \frac{2(1 - e^{-\kappa_\xi \tau})}{\kappa_\xi} + \frac{1 - e^{-2\kappa_\xi \tau}}{2\kappa_\xi} \right], \\ \omega_{r\xi}(\tau) &= \frac{\eta_r \eta_\xi \rho_{r\xi}}{\kappa_r \kappa_\xi} \left[\tau - \frac{1 - e^{-\kappa_r \tau}}{\kappa_r} - \frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi} + \frac{1 - e^{-(\kappa_r + \kappa_\xi) \tau}}{\kappa_r + \kappa_\xi} \right]. \end{aligned} \quad (12)$$

Proposition 1 The value of firm i 's risky zero-coupon bond is

$$P_t^i = K R(r_t, \xi_t, \tau) N(d_2) + V_t^i R(r_t, \xi_t, \tau) e^{M_i(r_t, \tau) + S_i^2(\tau)/2} N(-d_1), \quad (13)$$

where

$$d_1 = \frac{\ln(V_t^i/K) + M_i(r_t, \tau) + S_i^2(\tau)}{S_i(\tau)}, \quad d_2 = d_1 - S_i(\tau),$$

and

$$\begin{aligned} M_i(r_t, \tau) &= \left(\frac{\alpha_r}{\kappa_r} - \frac{\eta_r^2}{\kappa_r^2} - \frac{\sigma^2}{2} - \frac{\beta_i \sigma_V \eta_r \rho_{Vr}}{\kappa_r} \right) \tau + \left(\frac{\eta_r^2}{2\kappa_r^3} + \frac{\beta_i \sigma_V \eta_r \rho_{Vr}}{\kappa_r^2} \right) (1 - e^{-\kappa_r \tau}) \\ &\quad + \left(\frac{r_t}{\kappa_r} - \frac{\alpha_r}{\kappa_r^2} + \frac{\eta_r^2}{\kappa_r^3} - \frac{\eta_r^2}{2\kappa_r^3} e^{-\kappa_r \tau} \right) (1 - e^{-\kappa_r \tau}) \\ &\quad - l_i \left[\omega_{r\xi}(\tau) + \frac{\beta_i \sigma_V \eta_\xi \rho_{V\xi}}{\kappa_\xi} \left(\tau - \frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi} \right) \right], \end{aligned} \quad (14)$$

$$\begin{aligned} S_i^2(\tau) &= \left(\frac{\beta_i \sigma_V \eta_r \rho_{Vr}}{\kappa_r} + \frac{\eta_r^2}{\kappa_r^2} + \sigma^2 \right) \tau - \left(\frac{\beta_i \sigma_V \eta_r \rho_{Vr}}{\kappa_r^2} + \frac{2\eta_r^2}{\kappa_r^3} \right) (1 - e^{-\kappa_r \tau}) \\ &\quad + \frac{\eta_r^2}{2\kappa_r^3} (1 - e^{-2\kappa_r \tau}). \end{aligned} \quad (15)$$

The derivation is given in the Appendix. Equation (13) also makes the relation to familiar structural models transparent. Setting $l_i = 0$ removes liquidity costs and leaves a stochastic-

interest-rate structural model closely related to Longstaff and Schwartz (1995).⁶ If the short rate is further held constant, the interest-rate terms embedded in $R(r_t, \xi_t, \tau)$, $M_i(r_t, \tau)$, and $S_i(\tau)$ cancel, leaving the Merton (1974) price $P_t^i = Ke^{-r\tau}N(d_2) + V_t^i N(-d_1)$. With stochastic rates, that cancellation is incomplete: $M_i(r_t, \tau)$ and $S_i(\tau)$ incorporate the covariance between firm value and the short rate, while R reflects both interest-rate and liquidity discounting.

2.3 Model-Implied Factor Loadings

Applying Itô's lemma to $P_t^i = P(V_t^i, r_t, \xi_t, t)$ and using equation (8) yields the return decomposition.

Proposition 2 *The instantaneous return of bond i in excess of the risk-free rate is*

$$\frac{dP_t^i}{P_t^i} - r_t dt = b_i^V \sigma_V dB_t^V + b_i^r \eta_r dB_t^r + b_i^\xi \eta_\xi dB_t^\xi + l_i \xi_t dt + de_t^i, \quad (16)$$

where the three systematic loadings are

$$b_i^V = \beta_i \frac{V_t^i}{P_t^i} N(-d_1) R(r_t, \xi_t, \tau) e^{M_i(r_t, \tau) + S_i^2(\tau)/2}, \quad (17)$$

$$b_i^r = -\frac{1 - e^{-\kappa_r \tau}}{\kappa_r} \frac{K}{P_t^i} N(d_2) R(r_t, \xi_t, \tau), \quad (18)$$

$$b_i^\xi = -\frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi} l_i. \quad (19)$$

The firm-specific return component is

$$de_t^i = \frac{\partial \ln P_t^i}{\partial \ln V_t^i} \sigma_i dB_t^{V,i}. \quad (20)$$

The credit loading b_i^V equals firm i 's systematic asset beta β_i times the bond-price elasticity with respect to firm value. The key credit-quality term in equation (17) is $N(-d_1)$. For a high-quality issuer, firm value is far above the default boundary, d_1 is large, and $N(-d_1)$ is close to zero; the bond price is therefore nearly insensitive to an asset-value shock, and b_i^V is close to zero. As the issuer approaches default, d_1 falls and $N(-d_1)$ becomes economically meaningful. The remaining positive terms in equation (17) scale this sensitivity: β_i measures the issuer's exposure to the systematic asset-value shock, while

⁶Longstaff and Schwartz (1995) extend the first-passage framework of Black and Cox (1976). We instead retain the maturity-default convention of Merton (1974). Thus, the $l_i = 0$ case does not reproduce their model exactly. The two models nevertheless share a related structural valuation framework with stochastic Vasicek interest rates and yield tractable solutions.

$(V_t^i/P_t^i)R(r_t, \xi_t, \tau)e^{M_i(r_t, \tau) + S_i^2(\tau)/2}$ converts the sensitivity of the default-state payoff into a bond-return exposure. The credit loading is thus larger for issuers that are closer to default and more exposed to the common asset-value shock.

Because bond prices fall when interest rates rise, we define the duration loading as $-b_i^r$ in our empirical estimation. It is the product of the maturity multiplier $(1 - e^{-\kappa_r \tau})/\kappa_r$ and the credit adjustment $KRN(d_2)/P_t^i$. Under the calibration used below, $\kappa_r = 0.03$, so interest rates mean revert slowly and the first bracket is approximately τ over economically relevant bond maturities. Maturity is therefore the first-order driver of the duration loading. The second bracket is a credit-related adjustment equal to the share of the bond price associated with the promised-payment state. For a high-quality issuer, $N(d_2)$ is close to one and this adjustment is close to one, so $-b_i^r$ is approximately the bond's maturity exposure. As credit quality deteriorates, $N(d_2)$ and the promised-payment share decline, attenuating interest-rate sensitivity; this adjustment is modest for bonds sufficiently far from default but becomes more important for distressed issuers.

The liquidity loading has the simpler form $-b_i^\xi = l_i[(1 - e^{-\kappa_\xi \tau})/\kappa_\xi]$. The liquidity state mean reverts much faster in our calibration, with $\kappa_\xi = 0.8$, so its maturity multiplier rises initially but quickly flattens toward $1/\kappa_\xi$. Because the empirical sample requires $\tau \geq 1$, maturity contributes mainly near the short end and adds progressively less at longer maturities. Consequently, the bond-specific loss-given-liquidation l_i is the principal source of cross-section variation in the liquidity loading, especially among bonds with moderate or long remaining maturities.

The empirical mapping has two loose ends. First, the same bond-price elasticity multiplies the systematic and idiosyncratic asset-value shocks, whereas the credit loading b_i^V includes β_i and therefore isolates the component that covaries across issuers. The idiosyncratic component in equation (20) remains in the bond-specific regression residual. Second, liquidity returns contain both innovations in the common liquidity state, $b_i^\xi \eta_\xi dB_t^\xi$, and the drift associated with the expected liquidity loss, $l_i \xi_t dt$. Because both components vary across bonds with l_i , and because the maturity multiplier in $-b_i^\xi$ is nearly flat over most of the sample's maturity range, the cross-section approximately identifies their combined return. The three loadings are nevertheless jointly disciplined by the structural model: default risk changes the recovery and promised-payment shares, while correlations among the systematic shocks enter $M_i(r_t, \tau)$ and $S_i^2(\tau)$.

3 Estimating the Three-Factor Model

We extract the credit, duration, and liquidity factor returns directly from the cross-section of corporate bond returns. For each month t , we estimate

$$R_t^i - r_{f,t} = \alpha_t + b_{i,t-1}^V R_t^{Credit} + (-b_{i,t-1}^r) R_t^{Duration} + (-b_{i,t-1}^\xi) R_t^{Liquidity} + \epsilon_t^i, \quad (21)$$

where the three model-implied loadings are determined before month t . The signs on the rate and liquidity loadings make larger values correspond to greater duration and illiquidity exposure. The three slopes are estimated jointly, so each factor return is identified by the cross-section return variation associated with its loading conditional on the other two loadings. This extraction is structurally disciplined because the relevant cross-section directions are determined by the model-implied loadings rather than selected from bond characteristics or latent statistical components.

The notation in equation (21) distinguishes the empirically extracted factor returns R_t^{Credit} , $R_t^{Duration}$, and $R_t^{Liquidity}$ from the continuous-time shocks in equation (16). The credit loading contains β_i and therefore isolates the component of firm-value exposure that is systematic across issuers; firm-specific asset innovations remain in ϵ_t^i . For liquidity, the cross-section coefficient approximately combines compensation for the predictable loss rate $l_i \xi_t dt$ with compensation for innovations $b_i^\xi \eta_\xi dB_t^\xi$, because both channels vary with the bond-specific illiquidity exposure l_i and the maturity multiplier in $-b_i^\xi$ is nearly flat over most of the sample's maturity range. Intuitively, each slope can be represented as the return on a factor-mimicking portfolio of excess bond returns whose weights are determined jointly by the three model-implied loadings.

3.1 Data Description

To estimate the model and the resulting factor loadings, we focus on bond issuers with equity listed on the NYSE, Nasdaq, or AMEX. Their financial statements and equity-market information allow us to measure issuer credit quality.

We obtain transaction data from TRACE Enhanced database, bond returns from WRDS Bond Return database, bond characteristics from Mergent FISD, equity data from CRSP, and issuer balance-sheet information from Compustat. The sample contains fixed-rate, dollar-denominated corporate bonds with at least one year of remaining maturity, and identified Rule 144A issues are excluded. WRDS returns must have a current end-of-month price in both the current and preceding months and a nonmissing current-month return. Bond returns are winsorized at the 1% and 99% percentiles. The liquidity exposure is the effec-

tive bid-ask spread implied by the Gamma measure of [Bao, Pan, and Wang \(2011\)](#). The preceding-month Gamma estimate must contain at least ten adjacent return pairs. All inputs are aligned to the information set available before the return month. Bond characteristics are measured at the preceding month-end. Annual Compustat information becomes eligible 120 calendar days after the fiscal-period end and is matched backward as of the preceding month-end. Monthly cross-sectional regressions include Fama–French 17-industry controls.

Our bond-level data are summarized in Table I, consisting of monthly bond prices, bond characteristics, and bond trading information. For pricing data, we directly use the month-end return and yield to maturity data from the WRDS Bond Returns database. Following the convention, we use the Fed Constant Maturity Treasury curve as the reference curve and calculate the credit spread as the difference between the corporate bond yield and the Treasury yield of the same maturity. BondBeta is the bond beta estimated from a bond-market CAPM over a rolling window of the preceding 24 months. Maturity is the bond’s time to maturity in years. Rating is a numerical translation of Moody’s rating, from 1 for Aaa to 21 for C. Age is the time since issuance in years. Coupon is the bond’s coupon payment in percent. Amount is the bond’s amount outstanding in billions of dollars. Gamma is the return-covariance illiquidity measure. Callable is one for bonds issued with callable options.

For issuer-level equity information, EquitySize is the logarithm of market capitalization and EquityBeta is the slope from a stock-market CAPM estimated with the issuer’s monthly excess returns over the preceding 60 months. Equity volatility is estimated from as many as five years of monthly returns, subject to a minimum of 24 observations. BM, Leverage, and AssetGrowth are all constructed from the latest eligible fiscal-year-end report: BM is book equity divided by fiscal-year-end market capitalization, Leverage is total short- and long-term debt divided by total assets, and AssetGrowth is the growth rate of total assets. These bond and issuer inputs determine the model-based loadings for credit (b_i^V), liquidity ($-b_i^\xi$), and duration ($-b_i^r$).

Overall, the estimation sample contains 912,247 bond-month observations for 23,520 bonds issued by 1,966 firms. Table I reports the corresponding summary statistics. The mean monthly bond return is 40 bps and the mean yield spread is 180 bps. The median rating is 8, corresponding to Moody’s Baa1 rating. Median remaining maturity is 6.13 years, median bond age is 3.32 years, and median amount outstanding is USD 600 million. The median Gamma measure is 0.13. The median credit, duration, and liquidity loadings are 0.01, 4.28, and 0.86, respectively.

3.2 Factor Estimation

To calibrate the model at the firm level, we first estimate firm asset value and asset volatility. Following the Moody’s KMV approach described by Kealhofer and Kurbat (2001), we estimate V^i and σ by solving the following nonlinear equations simultaneously,

$$E_t^i = V_t^i R(r_t, \xi_t, \tau) e^{M_i(r_t, \tau) + \frac{1}{2} S_i^2(\tau)} N(d_1) - K R(r_t, \xi_t, \tau) N(d_2) \quad \text{and} \quad \sigma_E = \frac{V_t^i}{E_t^i} \frac{\partial E_t^i}{\partial V_t^i} \sigma, \quad (22)$$

where E_t^i is the value of the firm’s equity, V_t^i is the asset value of the firm, r_t is the risk-free rate, σ_E is equity volatility, σ is the total volatility of firm i ’s asset value, K is the default boundary, and τ is the firm-duration horizon.

To estimate monthly factors, we use the bond monthly excess return as the dependent variable in equation (21). The right-hand-side loadings are predetermined. Equity value, bond information, and Gamma come from the preceding month-end, while annual accounting data enter only after the 120-day availability lag. The default boundary K is the sum of current and long-term debt, and equity volatility is measured from up to 60 preceding monthly equity returns, subject to a minimum of 24 observations. We proxy the bond’s loss-given-liquidation with the effective spread $l_i = 2\sqrt{\max(\gamma_i, 0)}$ calculated from Gamma at month $t - 1$.

Two duration inputs enter at different levels of the estimation. Firm duration summarizes the maturity structure of the issuer’s liabilities and enters the firm-level default-risk calculation. The issuer’s annual report separates debt due within one year from debt due in years two, three, and four. We assign these disclosed debt buckets maturities of 0.5, 1.5, 2.5, and 3.5 years, respectively, assign a ten-year maturity to the remaining long-term debt that cannot be allocated more finely, and calculate the debt-value-weighted average maturity. Bond duration instead enters the bond-level interest-rate loading. Because the closed-form structural model treats debt as a zero-coupon claim, we use each coupon bond’s modified duration as its zero-coupon-equivalent maturity.⁷

For the interest-rate process, we use $\alpha_r = 0.002$, $\kappa_r = 0.03$, $\eta_r = 0.01$, and $\rho_{Vr} = -0.25$. For the liquidity process, we set $\bar{\xi} = 1$, $\kappa_\xi = 0.8$, $\eta_\xi = 1.2$, $\rho_{V\xi} = -0.25$, and $\rho_{r\xi} = -0.40$, so $\alpha_\xi = \kappa_\xi \bar{\xi} = 0.8$.⁸ The risk-free rate is obtained from Kenneth French’s data library. With

⁷This mapping preserves the bond’s first-order price sensitivity to interest rates. For example, a coupon bond with an eight-year contractual maturity and a six-year modified duration is treated as a six-year zero-coupon-equivalent claim when calculating its bond-level duration loading. The approximation does not alter the bond’s contractual maturity and is distinct from firm duration, which summarizes the maturity structure of the issuer’s liabilities for the default-risk calculation.

⁸The parameters are annualized. Monthly AR(1) estimates over the estimation history imply $\alpha_r \simeq$

these inputs, we estimate asset value V_t^i and total asset volatility σ from equations (22) and then compute the three loadings. For every trading day in month t , the daily estimation uses the same predetermined bond-month loadings as the monthly estimation.

The model-based columns of Table II present the average returns of the three factors. From August 2002 through March 2025, the credit factor earns 29.8 bps per month with a t -statistic of 3.36, while the liquidity factor earns 5.4 bps with a t -statistic of 4.64. The duration factor earns 1.2 bps and is not statistically significant. Over the same sample at the daily frequency, credit and liquidity earn 1.15 and 0.29 bps, with t -statistics of 3.06 and 4.69; duration earns 0.08 bps with a t -statistic of 1.04.⁹

The FF (2020) columns of Table II report the same economic exposures under the cross-section normalization of Fama and French (2020). Within each monthly or daily cross-section, we demean bond returns and standardize each of the three predetermined loadings to have mean zero and standard deviation one before estimating the three slopes jointly. In the Fama–French interpretation, each slope is the return on a zero-investment long-short portfolio whose value of the corresponding standardized loading is one and whose values of the other standardized loadings are zero. Equivalently, the relevant unstandardized loading is one standard deviation above its cross-section mean, while the other loadings are at their means. At the monthly frequency, credit and liquidity earn 10.0 and 7.6 bps, with t -statistics of 3.55 and 4.27, while duration earns 3.2 bps with a t -statistic of 0.59. At the daily frequency, the corresponding credit, liquidity, and duration premiums are 0.42, 0.39, and 0.21 bps, with t -statistics of 3.74, 4.64, and 0.83. Credit and liquidity therefore remain statistically

0.0020, $\kappa_r \simeq 0.0306$, and $\eta_r \simeq 0.0095$ for the short rate. Analogous estimates for the cross-section average Gamma process imply $\kappa_\xi \simeq 0.85$ and $\eta_\xi \simeq 1.18$. We use rounded values and normalize the long-run liquidity level to one. Setting all three shock correlations to zero leaves the estimates nearly unchanged: credit earns 0.294% per month ($t = 3.34$), liquidity 0.054% ($t = 4.66$), and duration 0.013% ($t = 0.74$), compared with 0.298% ($t = 3.36$), 0.054% ($t = 4.64$), and 0.012% ($t = 0.73$) in the baseline. Correlation terms are multiplied by other parameters that are small, such as η_r , and enter both drift and variance expressions with partly offsetting effects. Such changes primarily shift loadings broadly across bonds while leaving their cross-section ranking largely intact, so factor identification is insensitive to these parameter choices. Reasonable perturbations to the other calibrated parameters likewise have little effect on the estimated factors.

⁹Following Dickerson, Robotti, and Rossetti (2026), we re-estimate the model using their corrected monthly OSBAP bond returns without winsorizing those returns. We construct the corresponding Gamma input separately from their corrected daily transactions using the same adjacent-return procedure as in the baseline. From September 2002 through March 2025, the resulting credit and liquidity factors earn 26.7 and 4.7 bps per month, close in magnitude to the baseline estimates of 29.8 and 5.4 bps. Their t -statistics are 1.79 and 2.03, however, lower than in the WRDS baseline because the corrected returns retain extreme observations that conventional cleaning or winsorization may attenuate. In a stricter trading-activity specification that further requires lagged average daily par volume of at least \$100,000, the corresponding credit and liquidity t -statistics rise to 1.95 and 2.10. This additional screen reduces the influence of bond-months supported by small or infrequent transactions, which may be more sensitive to idiosyncratic transaction noise.

significant under both constructions.¹⁰

As illustrated in Figure 1, panel (a) plots the cumulative returns of the three monthly factors for credit, liquidity, and duration. Panel (b) displays the cumulative returns for the daily factors. Overall, we observe a high correlation between monthly and daily cumulative returns for each of the three factors. By running the cross-sectional regression specified in equation (21), our credit factor captures the average return, with greater weight assigned to issuers exhibiting higher credit risk. Likewise, the liquidity factor captures the average return, with more weight attributed to bonds with higher liquidity risk. The duration factor captures the average return weighted more heavily by bonds with longer duration. Therefore, we expect the three factors to have positive returns in normal market conditions. However, during market turmoil, as investors may sell high credit risk bonds and seek quality in bonds with low credit risk (flight-to-quality), the credit factor should experience negative returns. This intuition aligns with our empirical findings. Indeed, while the credit factor carries positive returns for most of the time, it becomes significantly negative during the 2008 financial crisis, the 2016 junk bond closure, and the 2020 COVID-19 pandemic. For the liquidity factor, the negative periods include 2008, 2016 and 2020. The duration factor is less volatile than the credit and liquidity factors, with the general increasing trend stopping after the 2020 pandemic and switching to a decreasing trend after the 2022 interest rate hike, similar to the pattern observed for U.S. Treasury bonds.

Over the full monthly sample, credit and liquidity move together because deterioration in issuer fundamentals often coincides with tighter dealer capacity and selling pressure on less liquid bonds. Duration captures a different interest-rate dimension. Its relation with credit reflects the balance between refinancing-cost shocks and flight-to-quality episodes, while its relation with liquidity reflects the tendency of Treasury duration returns to rise when corporate-bond liquidity deteriorates. The three factors therefore separate economically different sources of fixed-income risk even though those risks interact in periods of stress.

Figure 2 plots the normalized daily returns of the credit, liquidity, and duration factors and identifies the ten most negative realizations of each. These extreme returns help identify episodes of flight-to-quality, flight-to-liquidity, and dash-for-cash. In certain episodes, several factors fall sharply, revealing multiple forms of stress at the same time. During Lehman’s September 2008 collapse, credit and liquidity fell together, capturing simultaneous flight-to-

¹⁰The model-based premium corresponds to moving an economically defined model-implied loading from zero to one while holding the other loadings fixed. The standardized factor instead measures a one-standard-deviation cross-section change and has a zero-investment long-short interpretation. Within a given cross-section, a fixed rescaling changes the slope and its standard error proportionally. Because the cross-section standard deviations vary over time here, the time-series t -statistics of the average premiums need not be identical; Table II shows that the statistical conclusions are similar under the two normalizations.

quality and flight-to-liquidity. During the March 2020 COVID-19 selloff, all three factors experienced extreme negative returns on different days: credit on March 12 and 18, duration on March 17 during the dash-for-cash, and liquidity on March 23. The 2022 inflation and tightening cycle also affected all three: liquidity fell on May 9, while credit and duration fell together on June 13 after a hot CPI reading. Banking stress in 2023 appeared in credit and liquidity in March and in duration on May 1, when First Republic failed amid expectations of further Fed tightening. In other cases, the extreme response is concentrated in one factor, allowing us to identify events specific to each risk: the October 2002 post-dot-com stress in credit, the May 2010 Flash Crash in liquidity, and the June 2013 taper tantrum in duration. The joint extraction therefore shows both when several risks intensify together and when one risk dominates an episode.

3.3 Key Macro and Market Uncertainty Drivers

Next we delve into the drivers of our model-based bond factors. Specifically, we examine the time-series relationships between our three factors – credit, liquidity, and duration – and key macroeconomic and market variables. For macroeconomic uncertainty, we utilize the macro uncertainty index, financial uncertainty index, and real uncertainty index developed by [Jurado, Ludvigson, and Ng \(2015\)](#). These indices provide a comprehensive measure of the overall economic and financial uncertainty in the market. For market-based variables, we employ the VIX index from the CBOE to gauge stock market uncertainty, the MOVE index to assess Treasury market uncertainty, and the noise measure from [Hu, Pan, and Wang \(2013\)](#) to measure Treasury market liquidity. As shown in Table III, we conduct individual and joint regressions to determine which uncertainty measures have the strongest explanatory power for each factor. The regression results are presented in Panel A for the credit factor, Panel B for the liquidity factor, and Panel C for the duration factor.

Our findings reveal that the credit factor is negatively related to changes in the VIX index, financial uncertainty index, and MOVE index, with the VIX emerging as the strongest indicator. This suggests that credit risk is highly sensitive to broad market volatility and financial uncertainty. The liquidity factor is negatively related to changes in financial uncertainty and the VIX, consistent with tighter market liquidity when financial conditions deteriorate and intermediary balance-sheet costs rise. Macro uncertainty has a weaker negative relation with liquidity, while neither MOVE nor Treasury noise explains liquidity after controlling for the other measures. The duration factor is most strongly and consistently associated with the MOVE index, which specifically measures interest rate uncertainty – an intuitive alignment given duration’s sensitivity to rate movements. Overall, the results show

that the three factors map into distinct uncertainty dimensions: broad market and financial uncertainty for credit and liquidity, and interest rate uncertainty for duration.

3.4 Duration Factor and Interest Rates

The duration factor also maps directly into long-term interest-rate movements. Panel A of Figure 3 compares its cumulative return with the three-month Treasury bill rate and the 10-year constant-maturity Treasury yield. A duration-exposed bond loses value when its yield rises, so the model predicts that the factor should covary negatively with long-term yield changes. This comparison provides an external validation of the economic content of the cross-section loading.

Panel B reports the corresponding time-series relation. In a joint regression on monthly yield changes, duration loads strongly and negatively on the 10-year yield change but positively on the three-month yield change; the coefficients are -0.865 and 0.187 , with t -statistics of -16.02 and 2.33 , respectively. The regression explains 61% of monthly duration-factor variation. Because short- and long-term yields frequently move together, the joint specification separates the factor’s long-rate exposure from concurrent movements at the short end of the curve. The dominant negative coefficient on the 10-year yield supports the interpretation of the duration factor as compensation for long-term interest-rate risk.

The decomposition is also closely related to the duration-based valuation framework of [van Binsbergen, Nozawa, and Schwert \(2025\)](#). Over the common August 2002–December 2020 sample, our credit factor has a correlation of 0.69 with their duration-adjusted corporate-bond component, while our duration factor has a correlation of 0.72 with their duration-matched Treasury component. The two approaches therefore recover closely related credit and interest-rate return directions despite using different constructions.¹¹

3.5 Liquidity Factor and Dealer Balance-Sheet Capacity

Figure 4 next relates liquidity-factor risk to intermediary capacity. Panel A plots the exponentially weighted moving-average volatility of daily credit, liquidity, and duration returns over a three-month window, using a decay parameter of 0.98. Liquidity volatility measures instability in the cross-section price of liquidity exposure: it rises when otherwise similar

¹¹The raw premium magnitudes are not directly comparable because our factors price one unit of model-implied exposure, whereas the components of [van Binsbergen, Nozawa, and Schwert \(2025\)](#) are market-portfolio returns. The correlations are more informative about their shared economic content and remaining differences: their method subtracts duration-matched benchmark returns, whereas ours estimates the duration direction from model-implied cross-section loadings jointly with credit and liquidity.

bonds with different trading costs experience unusually different returns. The series reaches its sample peak during the March 2020 dash-for-cash, when corporate-bond market making was under exceptional strain.

Panel B relates liquidity volatility to primary dealers’ net positions in investment-grade and high-yield corporate bonds. Dealer-position data are comparable from April 2013 through March 2025.¹² Liquidity volatility is negatively related to dealer inventories ($t = -4.05$, $R^2 = 0.28$). Thus, periods in which dealers hold fewer corporate bonds are also periods in which the return payoff associated with model-implied liquidity exposure is more volatile. The relation is contemporaneous and does not by itself establish causality, but it connects the behavior of the liquidity factor to the balance-sheet capacity of intermediaries that warehouse corporate-bond risk.

4 Empirical Asset Pricing Tests

This section uses the three model-based factors for two complementary empirical tests. First, we ask whether they explain aggregate returns across asset classes. Second, we use the model-implied credit, liquidity, and duration exposures as a diagnostic tool for identifying the economic sources of returns on commonly used corporate-bond portfolios.

4.1 Explaining Aggregate Returns Across Asset Classes

For each market return, we estimate the monthly regression

$$R_t^M - R_t^f = \alpha + \beta^{\text{Credit}} R_t^{\text{Credit}} + \beta^{\text{Liquidity}} R_t^{\text{Liquidity}} + \beta^{\text{Duration}} R_t^{\text{Duration}} + \epsilon_t, \quad (23)$$

where R_t^{Credit} , $R_t^{\text{Liquidity}}$, and R_t^{Duration} are the factor returns extracted in Section 3. Table IV considers U.S. and foreign corporate-bond portfolios, U.S. high-yield and investment-grade bonds, equities, Treasuries, emerging-market U.S.-dollar bonds, and European government bonds. The U.S. and foreign corporate-bond returns are lagged-amount-weighted portfolios of bonds issued by U.S. and non-U.S. firms, respectively, and the equity return is the CRSP value-weighted market excess return from Kenneth French’s website. The remaining return series are drawn from the Bloomberg U.S. Corporate High Yield Index, U.S. Corporate Investment Grade Index, U.S. Treasury Index, Emerging Markets USD Sovereign Index, and Pan-European Aggregate Treasury Index.

¹²Before April 2013, the Federal Reserve did not separately report net positions in investment-grade and high-yield corporate bonds, instead publishing broader categories that included other bond types.

Panel A shows that the average excess returns are economically important for most risky markets. They are 35 bps per month for U.S. corporate bonds, 53 bps for high-yield bonds, 26 bps for investment-grade bonds, and 82 bps for equities. Foreign corporate bonds and emerging-market sovereign bonds earn 41 and 43 bps per month, respectively. U.S. Treasury excess returns are smaller and statistically insignificant. Panel B first isolates duration exposure. Duration alone explains 59% of aggregate corporate bond return variation, 71% of investment-grade bond variation, and 59% of Treasury variation, but leaves economically important alphas in most risky markets. Panel C adds credit. Credit loadings are large for high-yield bonds and equities and negative for Treasuries, consistent with flight to quality. The two-factor specification raises the R^2 to 72% for aggregate corporate bonds, 75% for investment-grade bonds, 50% for equities, and 71% for Treasuries.

Panel D reports the full three-factor model. The alphas fall to 9 bps for aggregate U.S. corporate bonds, 7 bps for high-yield bonds, 6 bps for investment-grade bonds, and 8 bps for equities, none of which is statistically significant. The same pattern holds for foreign corporate and sovereign bonds. Liquidity provides additional explanatory power for investment-grade and foreign corporate bonds. Treasury returns retain a positive alpha of 16 bps while loading positively on duration and negatively on credit.

4.2 The Model-Based Factor Model as a Diagnostic Tool

We next use the factor model as a diagnostic tool for the economic sources of returns within the corporate bond market. The analysis asks not only whether the model reduces portfolio alphas, but also whether the estimated credit, liquidity, and duration exposures reveal which risks drive characteristic-sorted returns. We examine 30 value-weighted portfolios formed by sorting bonds into quintiles on yield spread, credit rating, Bond CAPM beta, duration, illiquidity, and bond volatility. These portfolio families are commonly used corporate-bond test assets. Table V reports their mean excess returns and the alphas and loadings from the three-factor model. The raw monthly returns range from 12 to 55 bps and are statistically significant for most portfolios. After controlling for the three factors, 29 of the 30 alphas are statistically insignificant at the 5% level. The sole exception is the highest-rated portfolio. For the remaining portfolios, the factor model reduces economically large average returns to small residuals.

Similar to the credit spread puzzle of [Huang and Huang \(2012\)](#), the significant three-factor alpha of the highest-rated portfolio (Q1) reflects a model limitation, driven by the Gaussian mapping between the distance-to-default and the risk-neutral default probability. In particular, for the highly-rated bonds, their distance-to-default is many standard-

deviations away from zero, making the model-implied risk-neutral default probability close to zero. From this perspective, the model – incapable of pricing in the tail events – treats such highly-rated bonds as if they were default free. By contrast, the empirically observed market prices do price in the rare, correlated default losses implicit in the highly-rated bonds. In the credit spread puzzle of [Huang and Huang \(2012\)](#), the model understates the credit spread. In our setting, the model understates the loading on the credit factor, driven by $N(-d_1)$. As shown in Table V, the highly-rated bonds in Q1 have an average model-based credit loading of 0.015 in our sample, consistent with $N(-d_1)$ being close to zero for issuers with large distance-to-default. From this perspective, our empirical finding offers a unique cross-sectional counterpart to the credit spread puzzle of [Huang and Huang \(2012\)](#), linking the pricing of the highly-graded and high-yield bonds more closely via the model. Moreover, our result shows that liquidity risk helps attenuate, but does not eliminate this extra alpha. Specifically, the three-factor model reduces Q1’s mean excess return to a residual alpha roughly half as large, with liquidity exposure accounting for an important share of that reduction.

Our model-based factors also provide a diagnostic tool for identifying the economic drivers of characteristic-sorted portfolio returns. We examine portfolios sorted on yield spread, duration, and bond volatility, which [Kelly, Palhares, and Pruitt \(2023\)](#) identify as especially informative. Our model-based factor loadings of these empirically motivated portfolios reveal that the portfolios sorted by yield-spread and bond-volatility have increasing credit and liquidity exposures, while the duration-sorted portfolios have increasing duration exposure. Specifically, as shown in Table V, across yield-spread portfolios, the credit loading rises from -0.13 in the narrowest-spread quintile to 1.35 in the widest-spread quintile, while the liquidity loading rises from 1.20 to 4.94 . Across duration portfolios, the duration loading rises from 0.93 to 10.56 . Bond-volatility portfolios likewise display increasing credit and liquidity exposures. Thus, the credit and liquidity factors account for the return patterns across yield-spread and bond-volatility portfolios, whereas the duration factor accounts for the return pattern across duration portfolios. All alphas for these three portfolio families are insignificant at the 5% level, although Q2 of the bond-volatility sort has a marginally significant alpha of 10 bps at the 10% level.¹³

The remaining sorts reinforce the same economic ordering. Across rating portfolios, the credit loading rises from -0.10 for the highest-quality bonds to 1.20 for the lowest-quality

¹³This marginal significance is not robust to shortening the volatility window. When bond volatility is calculated from returns over the preceding 12 months, again requiring at least 10 observations, the five portfolio alphas are 6, 9, 10, 7, and -6 bps, with t -statistics of 1.55, 1.33, 1.22, 0.83, and -0.47 ; none is statistically significant.

bonds, and across bond-beta portfolios it rises from 0.09 in the lowest-beta quintile to 0.75 in the highest-beta quintile. Across illiquidity portfolios, the liquidity loading rises from 1.52 to 5.21. Together, the alpha reductions and ordered loadings show how the factor model operates as a diagnostic tool by linking characteristic-sorted portfolio returns to specific economic risk exposures.

5 Applications of the Model-Based Factors

The model-based factors provide a disciplined way to separate risks that are combined in observed fixed-income returns. We develop four applications. The first decomposes Treasury returns into duration risk and a return-based Safety Premium. The second decomposes corporate credit spreads into credit and liquidity components and uses their distinct relations with duration to revisit the relation between corporate credit spreads and Treasury yields. The third examines how interest-rate conditions propagate to subsequent credit and liquidity outcomes. The fourth distinguishes the predictive content of investment-grade and high-yield credit conditions for future corporate-bond liquidity.

5.1 $UST = \text{Duration Risk} + \text{Safety Premium}$

Treasury returns reflect both compensation for interest-rate exposure and the special value investors attach to Treasury safety. To separate these components, we apply the same model-implied loading and cross-section pricing method to two markets. The cross-section of investment-grade corporate bonds, after controlling for credit and liquidity, identifies a corporate duration factor. The cross-section of Treasury securities identifies a Treasury duration factor. Importantly, both objects are, by construction, returns to the same systematic interest-rate shock dB_t^r . Changing the test assets changes the cross-section used to estimate the price of that shock, but not the economic object being priced. Treasury duration is therefore the appropriate comparison for corporate duration.

Treasury duration contains the common interest-rate component captured by corporate duration together with the return benefit specific to Treasury safety. We define

$$R_t^{Safety} = R_t^{USTDuration} - R_t^{CorpDuration}.$$

This difference is a return-based Safety Premium. Over August 2002–March 2025, Treasury duration has a correlation of 92% with the aggregate U.S. Treasury excess return and a correlation of −94% with the monthly change in the 10-year Treasury yield. The latter sign

follows from the inverse relation between Treasury prices and yields.

Figure 5 illustrates the decomposition. Panel A compares the cumulative Treasury and corporate duration returns. Their persistent common movement reflects the interest-rate component shared across the two markets, whereas their divergence identifies variation in Treasury-specific safety. Panel B plots the cumulative return difference together with the Treasury basis of [Jiang, Krishnamurthy, and Lustig \(2021, 2023\)](#), a yield-based measure of the convenience value of Treasuries constructed from currency-hedged sovereign yield differentials. Despite their different units and construction, the two series display similar movements around major safe-asset-demand episodes. The return-based measure therefore complements the Treasury basis while avoiding cross-country investor clientele differences. This decomposition connects the return evidence to the broader safe-asset-demand literature. Our contribution is to isolate, within returns, the part of Treasury performance that is distinct from compensation for the same systematic duration shock priced in corporate bonds.

Table VI examines how the two components relate to returns in other markets. Corporate duration is positively associated with stock, investment-grade, and high-yield excess returns in univariate regressions, whereas the Safety Premium is negatively associated with all three. In the joint regressions, the Safety Premium remains economically and statistically important for stocks and high-yield bonds; both components matter for investment-grade bonds. Treasury returns load positively on both corporate duration and the Safety Premium, consistent with Treasuries reflecting common interest-rate risk and Treasury-specific safety value.

Figure 6 uses the daily joint realizations of corporate duration and the Safety Premium to distinguish stress regimes. A negative corporate duration realization indicates a dash-for-cash or an abrupt increase in interest-rate risk. Conditional on that movement, a positive Safety Premium identifies flight into Treasury safety, whereas a negative Safety Premium identifies flight away from Treasury safety. The global financial crisis, the August 2011 sovereign downgrade, and the September 2022 gilt-market spillover feature strong movements toward safety. By contrast, the days on which both duration and safety values collapse are concentrated in March 2020, when investors liquidated even Treasury securities to obtain cash. This joint decomposition separates conventional flight-to-safety episodes from the more unusual dash-for-cash state.

5.2 Credit Spread = Credit + Liquidity

A well-known feature of fixed-income markets is the negative relation between corporate credit spreads and long-term interest rates. [Longstaff and Schwartz \(1995\)](#) provide a struc-

tural explanation in which default risk interacts with a common interest-rate component. In their model, a higher short rate raises the risk-neutral drift of firm value, reduces the probability of default, and narrows the default-related component of credit spreads. Observed credit spreads, however, contain information about both credit and liquidity. Our duration factor captures the common interest-rate component of long-term bond returns, while the credit and liquidity factors separate the two corresponding components embedded in corporate-bond returns. Their comovement therefore reveals how the credit and liquidity channels relate differently to long-term interest-rate risk.

Figure 7 displays these relations. The full-sample correlation between credit and duration is 0.39 ($t = 6.90$), whereas the correlation between liquidity and duration is -0.26 ($t = -4.50$). These correlations have different economic implications. A negative duration-factor return represents an increase in long-term interest rates and a decline in bond prices. Because credit and duration are positively correlated, such an interest-rate realization tends to be accompanied by a negative credit-factor return, indicating deteriorating credit conditions and a widening credit component of spreads. The credit channel therefore contributes a positive spread–rate relation. By contrast, the negative liquidity–duration correlation implies that the same increase in long-term rates tends to be accompanied by a positive liquidity-factor return. This relative outperformance of bonds with high liquidity exposure is consistent with easing market-liquidity conditions and a narrowing liquidity component of spreads.¹⁴ The liquidity channel therefore contributes a negative spread–rate relation.¹⁵

The credit and liquidity channels therefore work in opposite directions. The credit component moves contrary to the familiar negative relation between corporate credit spreads and long-term interest rates, whereas the liquidity component moves in the direction consistent with it. This decomposition provides a channel through which aggregate credit spreads can narrow as long-term rates increase even when issuer credit conditions deteriorate. More generally, changes in total credit spreads can mask offsetting movements in issuer fundamentals and market liquidity. Separating these components is therefore important for interpreting whether an observed spread movement reflects changes in default risk or market liquidity. Our evidence therefore calls for structural models of default with stochastic interest rates to also incorporate a liquidity component.

¹⁴This pattern is consistent with common market states: risk-off episodes combine Treasury rallies with deteriorating corporate-bond liquidity, whereas risk-on episodes combine Treasury selloffs with stronger capacity to absorb bond liquidity risk.

¹⁵Consistent with the liquidity component being an important driver of credit spreads, Li (2026) develops a complementary intermediary-demand channel: higher long-term rates strengthen life insurers’ balance sheets, increase their demand for corporate bonds, and lower credit spreads. This mechanism provides a concrete link from long-term rates to intermediaries’ capacity to absorb corporate-bond risk.

5.3 Duration-Driven Credit and Liquidity Risk

The post-COVID inflation surge and the recent sharp increase in long-term U.S. Treasury yields raise an important question of how higher long-term rates affect subsequent credit and liquidity conditions, especially for high-yield issuers. Distinguishing these outcomes is important because the same rate shock can operate through issuer fundamentals and through the market’s capacity to absorb corporate bonds. To examine this propagation, for each outcome Y , we estimate

$$Y_{t+1} = a + \beta R_t^{Duration} + \epsilon_{t+1}. \quad (24)$$

The one-month lead distinguishes this exercise from contemporaneous comovement. It asks whether the current duration return contains information about next month’s separately estimated credit or liquidity factor return. The specification is a reduced-form propagation test. To distinguish market segments, the credit and liquidity factors used as outcomes are estimated separately from investment-grade and high-yield bonds. Figure 8 reports the full-sample coefficients together with rolling estimates and 95% confidence intervals. Duration predicts the high-yield credit factor with a coefficient of 1.08 and a t -statistic of 3.43, whereas the coefficient for investment-grade credit is 0.38 and statistically insignificant ($t = 1.34$). Duration also predicts investment-grade liquidity with a coefficient of 0.11 ($t = 3.54$); the corresponding high-yield coefficient is 0.09 and less precisely estimated ($t = 1.83$).

The key distinction is between a contemporaneous valuation response and intertemporal propagation. Our test asks whether the current model-implied duration return predicts subsequent returns associated with separately identified credit and liquidity exposures. A significant slope therefore indicates that the effect of an interest-rate movement extends beyond its immediate mechanical effect on bond prices.

Because a negative duration return corresponds to an increase in long-term yields, the positive slopes imply that rising rates are followed by worse credit conditions, especially among high-yield issuers, and worse liquidity conditions, especially among investment-grade bonds. The results therefore separate two forms of propagation: a credit-quality response concentrated among riskier issuers and a market-liquidity response concentrated among investment-grade bonds.

5.4 Credit-Driven Liquidity Risk

The fourth application examines the dynamic relation between credit and liquidity risks. Contemporaneously, the two factors are positively correlated (0.54, $t = 10.58$), with the

comovement strengthening during crises and subsiding as the economy recovers. The correlation calculated over rolling 24-month windows peaks at 0.76 in April 2020 and subsequently declines to 0.02 by March 2025. This pattern is consistent with the structural models of [He and Xiong \(2012\)](#), [He and Milbradt \(2014\)](#), and [Chen et al. \(2018\)](#), which incorporate both credit-driven liquidity and liquidity-driven credit. Because it is difficult to identify the direction of causality from contemporaneous comovement, we examine the lead-lag relation. Specifically, we separate the predictive content of investment-grade and high-yield credit for the aggregate liquidity factor using the joint regression

$$R_{t+1}^{Liquidity} = a + \beta_{IG} R_t^{IG\ Credit} + \beta_{HY} R_t^{HY\ Credit} + \epsilon_{t+1}. \quad (25)$$

As shown in the top panels of [Figure 9](#), both credit factors have incremental predictive power. The investment-grade coefficient is 0.02 with a t -statistic of 2.68, and the high-yield coefficient is 0.03 with a t -statistic of 4.05; jointly, they explain 14% of the variation in next month's liquidity return. Deterioration in either segment of the credit market is therefore followed by weaker returns on bonds with greater exposure to liquidity risk.

To determine whether short-run predictability is subsequently offset, we also estimate the cumulative projection

$$\sum_{j=1}^k R_{t+j}^{Liquidity} = a_k + \beta_{IG}(k) R_t^{IG\ Credit} + \beta_{HY}(k) R_t^{HY\ Credit} + \epsilon_{t,k}, \quad k = 1, \dots, 36. \quad (26)$$

Here, $\beta_{IG}(k)$ and $\beta_{HY}(k)$ measure the cumulative conditional association with liquidity returns through horizon k , holding the other credit factor fixed. The bottom panels of [Figure 9](#) reveal distinct horizon patterns. The investment-grade coefficient rises gradually and remains positive over much of the 36-month horizon, indicating that the initial predictive relation is not quickly offset. The high-yield coefficient is positive at short horizons, peaks within the first several months, and then declines and reverses at longer horizons. Thus, high-yield credit contains stronger near-term information, whereas investment-grade credit contains a more persistent signal about aggregate corporate-bond liquidity.

This directional evidence complements structural models that emphasize the joint determination of credit and liquidity. Our evidence identifies an empirical asymmetry at the monthly factor-return frequency: investment-grade and high-yield credit each contain incremental information about subsequent liquidity, whereas liquidity does not reliably predict either credit factor.

6 Comparison with Existing Factor Models

Having established that our model-based factors explain risk premiums across markets and portfolios in Section 4, we now ask how they compare with the existing empirical and statistical factors in the corporate bond pricing literature. We run a horse race against eight benchmark models over their longest matched samples, beginning as early as August 2002. The benchmarks span the main approaches in the literature: return-based traded factors, an intermediary-based factor, a corrected corporate bond four-factor model, a duration-adjusted valuation model, and latent statistical factors.

We assess several questions in turn. First, we ask whether each model prices a common set of corporate bond portfolios and whether the ranking is robust to randomly selected test assets. Second, we compare the maximum Sharpe ratios of the factor spans and test whether our GP3 expands the investment opportunities available from the benchmark factors. Third, two-way spanning tests identify which components of our GP3 remain incremental to existing models and which benchmark return directions remain outside it.¹⁶

6.1 Factor Models and Test Assets

The first group contains low-dimensional traded factors. DJM1 is the value-weighted corporate bond market factor studied by [Dickerson, Julliard, and Mueller \(2023\)](#), and DJM2 augments it with the Treasury term factor. FF5 combines the equity market, size, and value factors with the term and default factors of [Fama and French \(1993\)](#). HKM2 contains the equity market and the traded intermediary-capital factor of [He, Kelly, and Manela \(2017\)](#).

DMR4 uses the corrected factor series of [Dickerson, Mueller, and Robotti \(2023\)](#) for the four-factor corporate bond model originally developed by [Bai, Bali, and Wen \(2019\)](#). It contains the corporate bond market factor together with downside-risk, credit-risk, and liquidity-risk factors. [van Binsbergen, Nozawa, and Schwert \(2025\)](#) develop duration-based models for equity and corporate bond returns. We use their two-factor corporate bond specification, denoted vBNS2, which separates the corporate bond market return into a duration-matched Treasury component and a duration-adjusted corporate bond component. Section 3.4 documents how these two components relate to our model-implied credit and duration factors.

¹⁶These criteria capture distinct dimensions of model performance. Time-series intercepts test whether a model prices individual portfolios and their joint return space. Cross-sectional regressions ask whether factor exposures explain average returns. Maximum Sharpe ratios compare the investment opportunities contained in the factor spans. We conduct every pairwise comparison on identical assets and months, restricting our GP3 to the available sample of the corresponding benchmark.

The final group contains latent-factor models. The IPCA model of [Kelly, Palhares, and Pruitt \(2023\)](#) allows corporate bond characteristics to determine time-varying factor loadings and extracts five common factors. We use the five-factor specification with $\Gamma_\alpha = 0$, so that characteristics affect expected returns through their factor exposures. The Regressed-PCA model of [Chen et al. \(2026\)](#)¹⁷ and the related framework of [Chen, Roussanov, and Wang \(2025\)](#) first isolate characteristic-predicted returns and then estimate common factors from the predicted and residual return components. We use the ten-factor specification with $a \neq 0$.

Table [VII](#) evaluates the models on the same 50 corporate bond portfolios.¹⁸ Our GP3 and the traditional traded factors begin in August 2002 and end in December 2022. DMR4 begins in August 2004, RPCA10 in July 2004, and IPCA5 in August 2003; their ending dates also differ. Each table reports the exact matched sample and number of observations.

For portfolio i and factor model m , we estimate

$$R_{i,t}^e = \alpha_{i,m} + \beta'_{i,m} \mathbf{f}_{m,t} + \epsilon_{i,m,t}. \quad (27)$$

Following the model-comparison approach of [Fama and French \(2020\)](#), we report the Gibbons, Ross, and Shanken joint-alpha test, the mean absolute alpha, and OLS and GLS cross-sectional R^2 .

6.2 Pricing Performance on Corporate Bond Portfolios

Panel A of Table [VII](#) shows that our GP3 performs competitively on the pricing-error measures for the 50 common corporate bond portfolios. From August 2002 through December 2022, its GRS p -value is 0.052, so the joint zero-alpha null is not rejected at the 5% level. Its mean absolute alpha is 8.6 bps per month, and its OLS cross-sectional R^2 is 0.916. The model therefore captures most of the dispersion in average returns with three economically identified factors.

The traded benchmarks have complementary strengths. DJM1 has a slightly higher GRS p -value of 0.067 and a mean absolute alpha of 8.0 bps, but its OLS R^2 is 0.601. Adding TERM in DJM2 raises the OLS R^2 to 0.930, close to our GP3. DMR4 performs particularly

¹⁷We thank the authors for providing their factor data.

¹⁸The 50 portfolios are the in-sample test assets constructed by [Dickerson, Julliard, and Mueller \(2023\)](#): 25 value-weighted portfolios double-sorted on credit spread and issue size and 25 double-sorted on rating and time to maturity. They form a compact common testing set rather than an exhaustive standard universe. The same data library contains 77 additional out-of-sample portfolios and 108 single-sorted corporate bond strategies. We use the broader 108-strategy universe in the random-portfolio tests below.

well on pricing-error magnitude and cross-sectional fit. Its mean absolute alpha of 5.1 bps is the smallest in the table, and its OLS and GLS R^2 values are 0.966 and 0.155. These results confirm that the corrected BBW4 factors capture important dimensions of corporate bond returns. The higher-dimensional statistical models also attain strong cross-sectional fit. RPCA10 has OLS and GLS R^2 values of 0.973 and 0.205, the highest in the table, while vBNS2 has an OLS R^2 of 0.949, confirming that its duration decomposition is informative for corporate bond returns.

The 50 portfolios provide a common benchmark, but model rankings can depend on the particular test assets. Panel B of Table VII therefore reports 10,000 common random selections of 20 portfolios from the 108 corporate bond strategies of Dickerson, Julliard, and Mueller (2023). Using identical draws for every model ensures that differences reflect factor performance rather than different portfolio selections.

The joint zero-alpha null is rejected in most random test-asset sets for every model, so these results provide a relative rather than an absolute ranking. Our GP3 has the lowest rejection frequency, 73.7%, compared with 82.7% for HKM2, 87.3% for DJM1, 89.0% for RPCA10, and at least 90.5% for the remaining models. Its mean GRS p -value of 0.046 is also the highest. The cross-sectional R^2 results identify a different strength. RPCA10 has an average OLS R^2 of 0.852, followed by IPCA5 at 0.756 and DMR4 at 0.677, compared with 0.593 for our GP3. Thus, our GP3 performs best on the relative joint-alpha criterion, whereas the latent models and DMR4 fit more of the dispersion in average returns across randomly selected portfolios.

Figure 10 summarizes the two panels of Table VII. Panels (a) through (c) compare joint-alpha performance, mean absolute pricing errors, and cross-sectional fit on the 50 common portfolios. Panel (d) reports GRS rejection frequencies across the random 20-portfolio draws. Our GP3 performs especially well on the random-set joint-alpha criterion, DMR4 on mean absolute pricing error, and RPCA10 on cross-sectional fit.

6.3 Maximum Sharpe Ratios

A factor model's maximum Sharpe ratio summarizes the best ex-post mean-variance trade-off in its factor span. For factor mean vector $\boldsymbol{\mu}_f$ and covariance matrix $\boldsymbol{\Sigma}_f$, the squared maximum Sharpe ratio is

$$SR^2 = \boldsymbol{\mu}_f' \boldsymbol{\Sigma}_f^{-1} \boldsymbol{\mu}_f. \quad (28)$$

Table VIII reports annualized maximum Sharpe ratios and the finite-sample correction of Barillas et al. (2020). Because the correction depends on the number of factors and observations, it is especially useful when comparing a three-factor model with higher-dimensional

alternatives. The nested and nonnested tests in the table answer different questions. The nested GRS test asks whether the GP factors have jointly zero intercepts relative to a benchmark. A small p -value therefore means that GP3 expands the benchmark investment opportunity set. The nonnested ΔSR^2 test compares the magnitudes of the two standalone factor frontiers. Its probability values are obtained from a centered circular block bootstrap with 12-month blocks and 10,000 draws.

Our GP3 has a larger annualized maximum Sharpe ratio than the low-dimensional traded benchmarks over the corresponding matched samples. From August 2002 through December 2022, its maximum Sharpe ratio is 1.084, compared with 0.613 for DJM1, 0.616 for DJM2, 0.763 for FF5, and 0.661 for HKM2. The finite-sample-adjusted value is 1.002, compared with adjusted benchmark values between 0.525 and 0.576. On the DMR4 sample, our GP3 has raw and adjusted annualized Sharpe ratios of 1.216 and 1.128, compared with 0.994 and 0.854 for DMR4. On the vBNS2 sample, the corresponding values are 1.115 and 1.026 for our GP3 and 0.999 and 0.934 for vBNS2.

The nested GRS probability values are at or below 0.004 for every traded benchmark. Thus, the incremental GP factor returns are jointly significant after controlling for each existing model, providing direct evidence that our GP3 expands their low-dimensional factor spans. The nonnested ΔSR^2 tests compare the standalone frontiers rather than asking whether our GP3 adds investment opportunities conditional on the benchmark. The point estimate for our GP3 exceeds each traded benchmark, while the equality probability values are between 0.314 and 0.798. Together, the results show that our GP3 contributes a significant incremental return direction and produces the higher estimated traded-factor frontier.

The maximum Sharpe ratios of the statistical models require separate interpretation. RPCA10 has a strong raw annualized factor-space Sharpe ratio of 1.268 and an adjusted value of 0.972, calculated from the ten released factor-mimicking returns over the matched sample. By contrast, IPCA5’s much larger in-sample factor-space Sharpe ratio reflects the geometry of an estimated latent factor space and should not be read as the realized performance of an immediately implementable trading strategy.

6.4 Two-Way Factor Spanning

Table IX examines factor spanning in both directions. Panel A regresses each GP factor on a benchmark. The joint GRS null that all three GP intercepts are zero is rejected for every benchmark. The individual intercepts show that liquidity is the main source of rejection. Against the traded benchmarks and RPCA10, the liquidity alpha is approximately 4 to 5 bps per month, with Newey–West t -statistics between 2.65 and 3.70. Credit alphas are

generally smaller: they are significant at the 5% level only against DJM2 and vBNS2, with DJM1 marginally significant at the 10% level. Duration has insignificant alphas relative to DJM1, HKM2, DMR4, and RPCA10, but significant negative alphas relative to DJM2, FF5, and vBNS2. Existing models therefore capture important credit-market and interest-rate variation, but the spanning patterns differ across benchmarks and none fully reproduces the return premium associated with the model-implied liquidity exposure. Panel B reverses the regressions and reveals which benchmark components remain outside our GP3. DJM1 is fully spanned, with a joint GRS p -value of 0.373. Our GP3 also spans HKM2 and DMR4, with joint p -values of 0.235 and 0.237, and none of the individual DMR4 intercepts is significant. Thus, the three structural factors absorb the priced return directions in the corrected four-factor bond model while retaining a separate liquidity premium in Panel A.

The specifications that are not fully spanned share a clear economic feature. For DJM2, the only significant individual intercept is TERM, with a t -statistic of 3.60. The same term component produces the largest intercept in FF5. For vBNS2, only its duration component has a significant intercept, with a t -statistic of 4.12. Thus, the reverse spanning rejections are concentrated in Treasury term and duration returns rather than in a broad failure to capture the benchmark models. The TERM intercept does not imply that the GP duration factor fails to capture ordinary interest-rate exposure. Table IV shows that Treasury returns load strongly and positively on the duration factor but negatively on the credit factor during flight-to-quality episodes. Controlling simultaneously for these components can therefore leave a positive Treasury term or safety-premium residual. The strict spanning rejection identifies this additional Treasury return component rather than a general failure of duration to measure interest-rate risk.

The latent-factor results have a similar concentration. The joint test rejects for RPCA10, but only two of its ten individual factors have significant intercepts. For IPCA5, three of the five factor intercepts are significant. These results recognize the additional directions available to the latent models. Together, the two panels identify the main distinction between the models: our GP3 contributes a liquidity return direction that is not absorbed by the benchmarks, while the remaining benchmark information is concentrated in term, duration, and a small subset of latent factors.

Overall, the tests deliver a consistent assessment. Our GP3 produces competitive joint pricing performance on the 50 portfolios, the strongest joint-alpha performance across random test-asset sets, a high low-dimensional factor frontier, and a liquidity premium that survives controls for existing traded and latent models. DMR4 provides especially small pricing errors, and DMR4 and the latent models achieve high cross-sectional fit. The contribution of our GP3 is to combine competitive performance with a parsimonious structural

decomposition of credit, liquidity, and duration risks.

7 Conclusion

This paper develops a model-based approach to extracting common credit, liquidity, and duration risks from U.S. corporate bond returns. We extend the Merton structural model of default to incorporate stochastic interest rates and a systematic liquidity risk. Cross-section regressions of excess bond returns on the resulting model-implied loadings recover the three factor returns. The estimated factors have distinct risk premia and economic content. From August 2002 through March 2025, credit earns 29.8 bps per month with a t -statistic of 3.36, and liquidity earns 5.4 bps with a t -statistic of 4.64. Duration earns 1.2 bps and is insignificant, but captures systematic exposure to long-term rates. Credit is most sensitive to the VIX, duration to long-term Treasury yields and interest-rate uncertainty, and liquidity to financial uncertainty and dealer balance-sheet capacity. These distinct empirical drivers reinforce the structural interpretation of the factors.

The extreme negative returns of the daily factors provide a complementary view of their economic content. Credit and liquidity fall together around Lehman’s collapse, identifying simultaneous flight-to-quality and flight-to-liquidity, while all three risks intensify during March 2020, the 2022 inflation cycle and 2023 banking stress. By contrast, post-dot-com stress is concentrated in credit, the May 2010 Flash Crash in liquidity, and the June 2013 taper tantrum in duration. The factors thus distinguish episodes in which several risks intensify together from those dominated by one risk.

Our factors also perform well in empirical asset-pricing tests. The three-factor model explains average excess returns across major risky asset classes, including corporate bonds, equities, and emerging-market sovereign bonds. It also leaves 29 of 30 characteristic-sorted corporate-bond portfolio alphas insignificant at the 5% level. As a diagnostic tool, the model attributes the yield-spread and bond-volatility patterns to credit and liquidity, and the duration-sort pattern to duration. It therefore identifies the economic origins of characteristic-based returns as well as reducing pricing errors.

The separation of the three risks yields four interesting applications. First, we decompose U.S. Treasury returns into a pure duration component and a safety component, showing that March 2020 is the only episode in which Treasuries lose both duration and safety value. Second, we decompose corporate credit spreads into credit and liquidity components and find that the negative correlation between credit spread and interest rate is driven by liquidity rather than credit. Third, rising long-term yields predict deteriorating high-yield credit and worsening investment-grade liquidity. Fourth, the lead-lag results show that investment-

grade and high-yield credit predict future aggregate liquidity, whereas liquidity does not reliably predict subsequent credit.

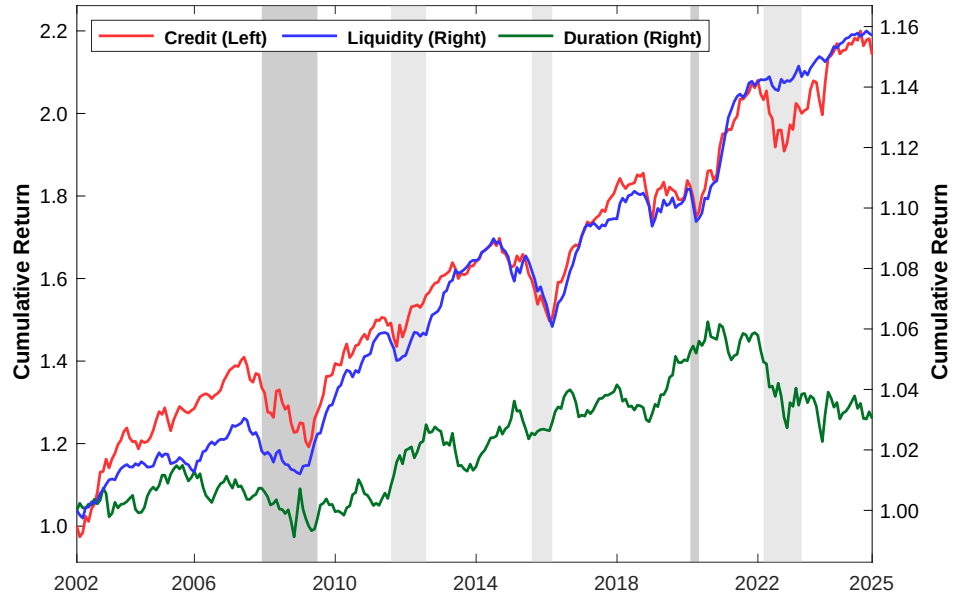
Finally, we show that our three-factor model is competitive with leading traded and statistical specifications, performs best on joint alphas across random test-asset sets, and has a higher maximum Sharpe ratio than low-dimensional traded benchmarks. Other models retain advantages on some pricing-error and cross-section-fit measures. The model therefore combines economic interpretation with competitive empirical performance.

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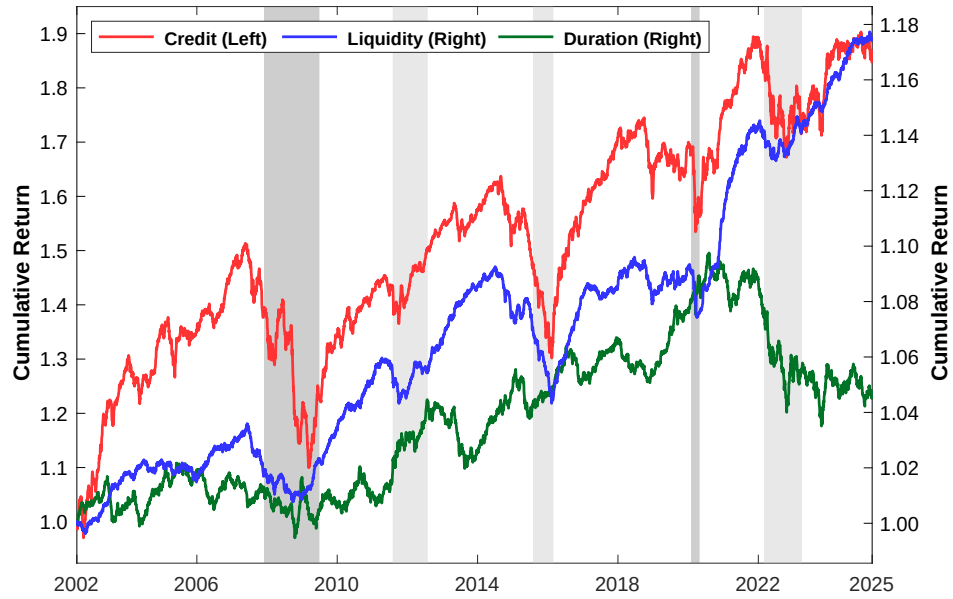
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(a) Monthly Cumulative Return



(b) Daily Cumulative Return

Figure 1. This figure plots the cumulative returns of the Credit, Liquidity, and Duration factors from August 2002 through March 2025 at a monthly frequency in Panel A and a daily frequency in Panel B. Each series is constructed by cumulatively summing the corresponding factor returns.

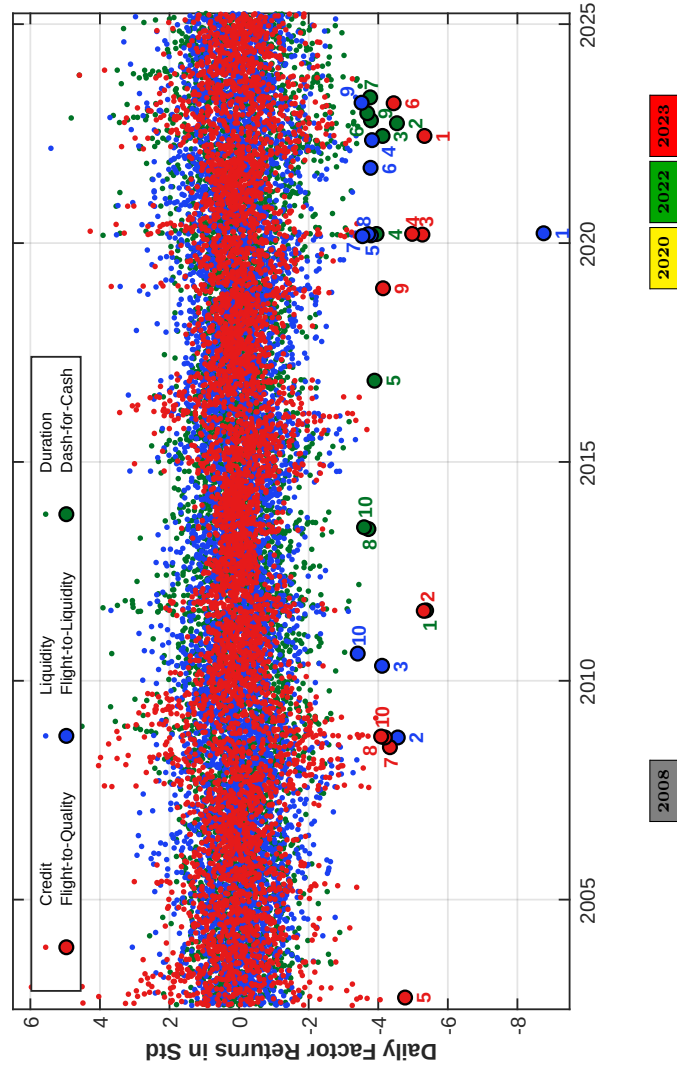
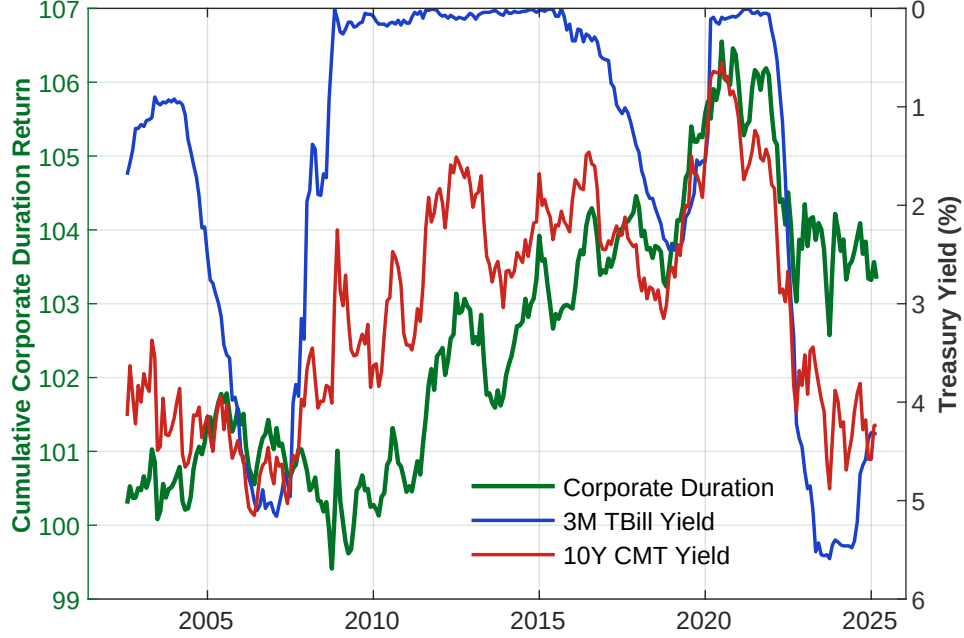


Figure 2. Normalized Daily Factor Returns and Extreme Events. The figure plots normalized daily Credit, Liquidity, and Duration factor returns from August 2002 through March 2025 and numbers the ten most negative realizations of each factor. The tables identify the corresponding dates, standardized moves, and principal market events.

Most Negative Duration-Factor Days		
Date	Std	Main event
1 2011-08-11	-5.38	Reversal: UST downgrade+European stress (8/5-10)
2 2022-09-27	-4.54	Hot CPI & Hawkish Fed+UK fiscal crisis
3 2022-06-13	-4.12	Hot CPI + upcoming FOMC on 6/15 (+75bp)
4 2020-03-17	-3.95	Peak dash-for-cash + CPFF/PDCF
5 2016-11-09	-3.89	Reversal: Trump won on 11/8
6 2022-10-21	-3.79	Reversal: Fed signals slowdown (Nov last +75bp)
7 2023-05-01	-3.72	Move FOMC (+25bp) tightening+FRB failure
8 2013-06-20	-3.68	BoJ surprise/boad selloff
9 2022-12-20	-3.59	Strong payrolls/Fed taper four
10 2013-07-05	-3.59	Strong payrolls/Fed taper four
Most Negative Credit-Factor Days		
1 2022-06-13	-5.33	Hot CPI + upcoming FOMC on 6/15 (+75bp)
2 2011-08-08	-5.31	UST downgrade (8/5 Friday)
3 2020-03-12	-5.27	Confined dash-for-cash & global sell-off
4 2020-03-15	-4.97	Confined dash-for-cash & global sell-off + MMLF
5 2022-10-07	-4.77	Post-dot-com stress
6 2023-05-13	-4.44	SVB banking stress
7 2008-06-26	-4.34	Pre-Lehman selloff
8 2008-09-15	-4.19	Lehman bankruptcy
9 2018-12-20	-4.14	Fed hike/growth fears
10 2008-09-23	-4.08	TARP uncertainty
Most Negative Liquidity-Factor Days		
1 2020-03-23	-8.75	QE infinite/PACCF/SMCCF
2 2008-09-15	-4.56	Lehman bankruptcy
3 2010-05-06	-4.11	Flash Crash/liquidity withdrawal
4 2022-05-19	-3.82	Inflation & aggressive rate hike (+50bp on 5/4)
5 2020-03-06	-3.79	COVID finding stress
6 2021-09-20	-3.78	Evergrande risk-off
7 2020-03-16	-3.71	Fed emergency cut and QE (3/15 Sunday)
8 2020-02-28	-3.55	COVID selloff
9 2023-05-13	-3.52	FRB banking stress and large banks' exposure
10 2010-08-16	-3.41	Growth/detention fears

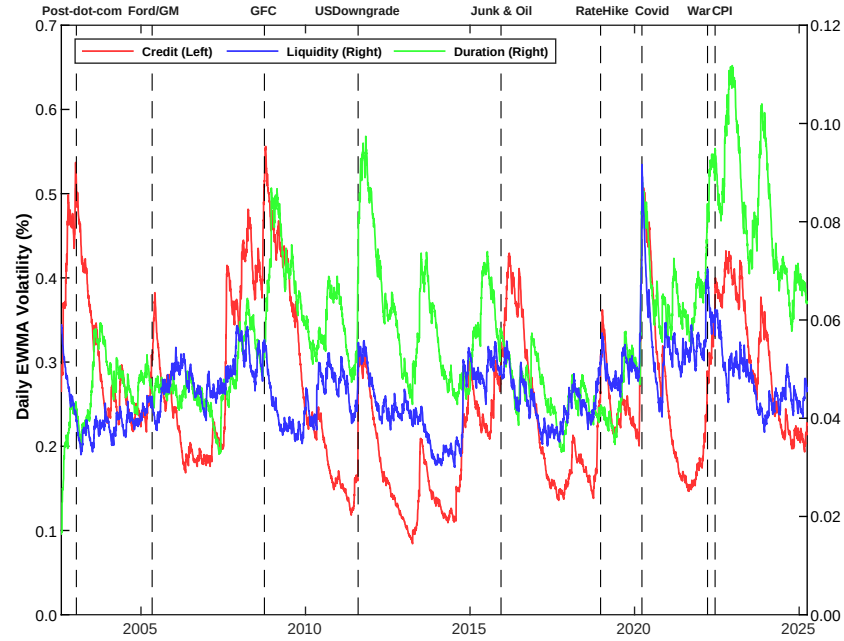


(a) Cumulative Corporate Duration and Treasury Yields

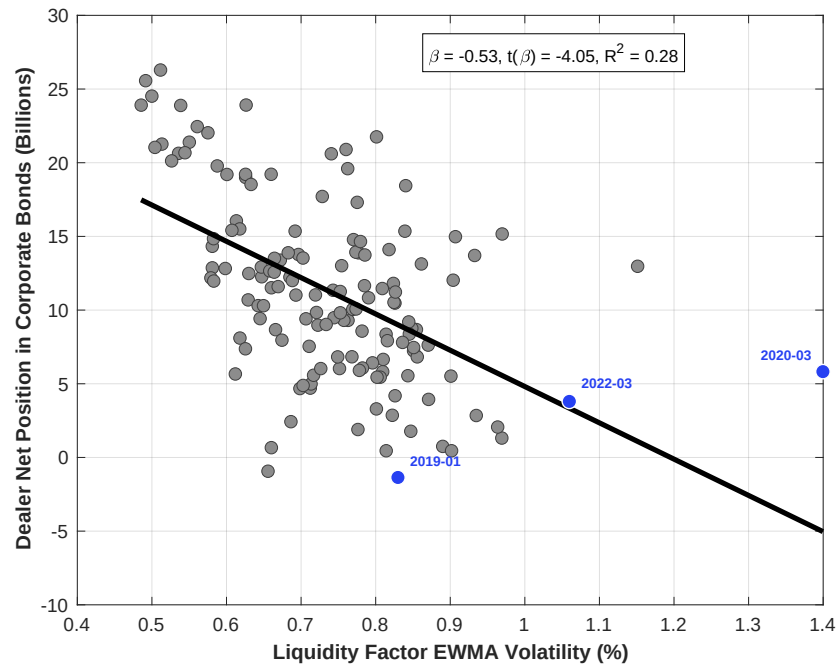
	Duration factor		
Constant	0.013 [0.83]	0.012 [1.13]	0.010 [0.99]
Δy^{3M}	-0.103 [-1.14]		0.187** [2.33]
Δy^{10Y}		-0.826*** [-14.60]	-0.865*** [-16.02]
R^2	0.006	0.592	0.610
Obs	272	272	272

(b) Duration Factor Regressions

Figure 3. The Duration Factor and Treasury Yields. Panel A plots the cumulative Corporate Duration return with the three-month Treasury bill rate and the 10-year constant-maturity Treasury yield. Panel B reports regressions of the monthly Duration return on changes in the two yields, separately and jointly. The sample spans August 2002 through March 2025. Square brackets contain t -statistics.

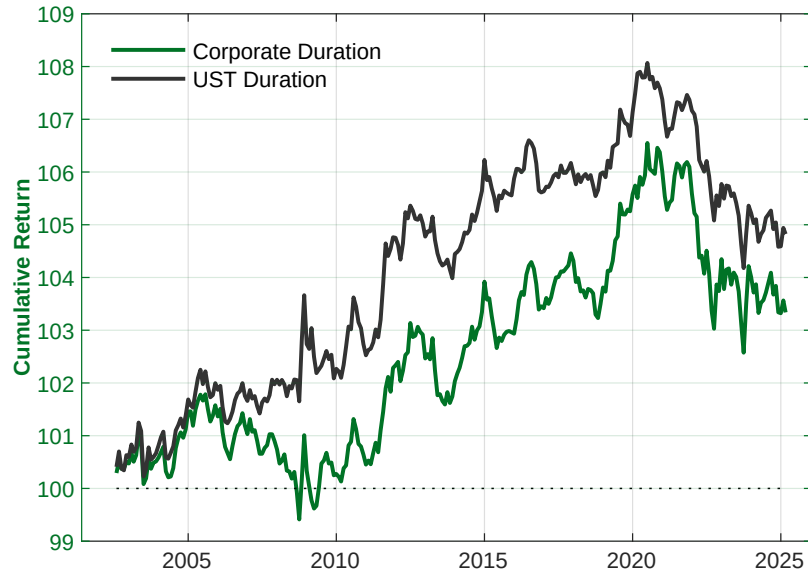


(a) Daily EWMA volatility

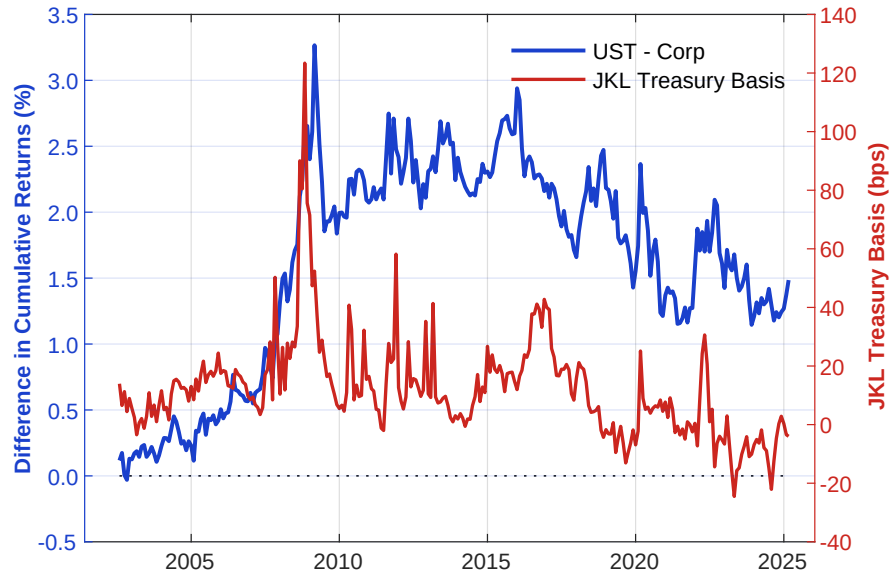


(b) Dealer net positions

Figure 4. Liquidity Risk and Intermediary Capacity. Panel A plots the exponentially weighted moving-average volatility of daily factor returns. Panel B relates Liquidity volatility to primary dealers' net positions in investment-grade and high-yield corporate bonds. The box reports the standardized slope, Newey–West t -statistic with 12 lags, and R^2 . The factor sample spans August 2002 through March 2025, and the dealer-position sample begins in April 2013.



(a) Cumulative Duration Return: UST vs. Corp



(b) Difference in Cumulative Duration Returns: UST – Corp

Figure 5. A Return-Based Convenience Yield of U.S. Treasuries. Panel A compares cumulative Treasury and Corporate Duration returns. Panel B plots their cumulative difference, which is the return-based Safety Premium, together with the Treasury basis of [Jiang, Krishnamurthy, and Lustig \(2021\)](#). The sample spans August 2002 through March 2025.

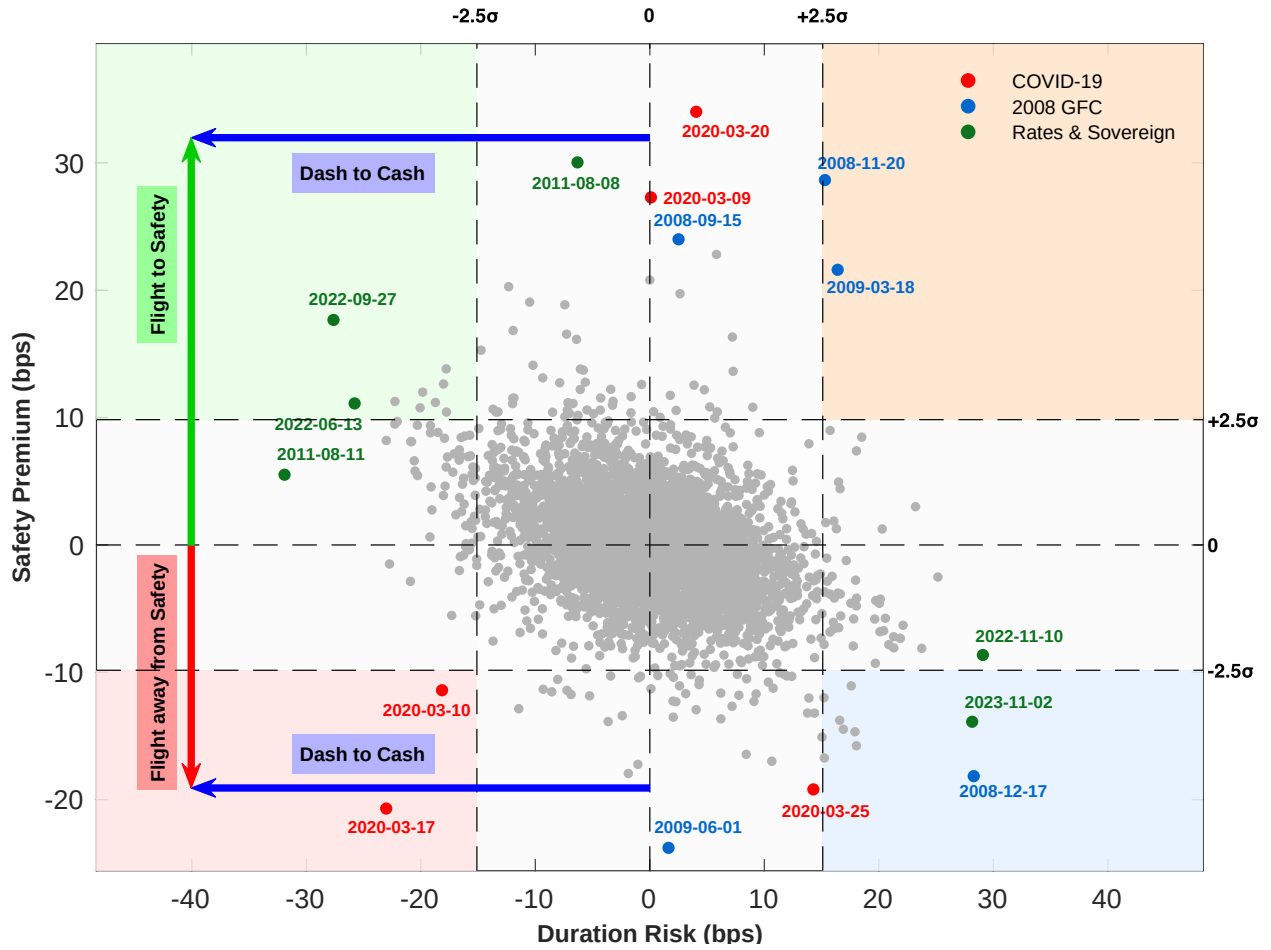
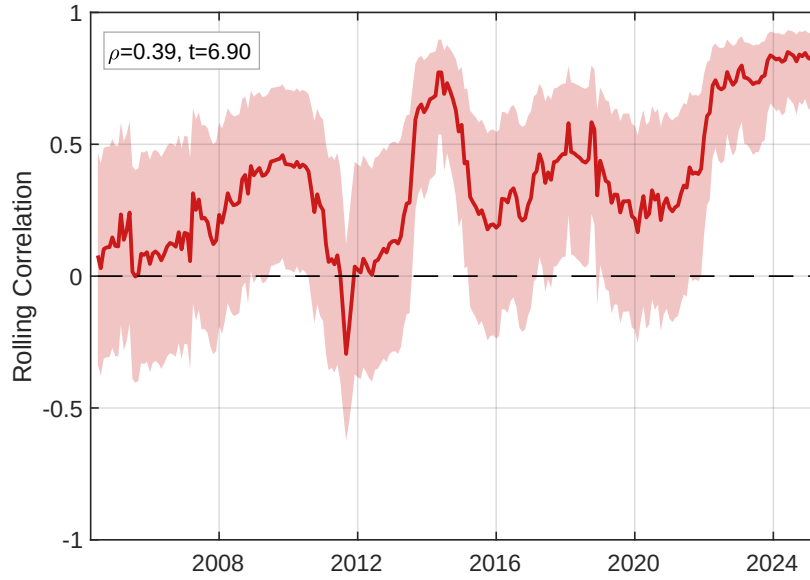
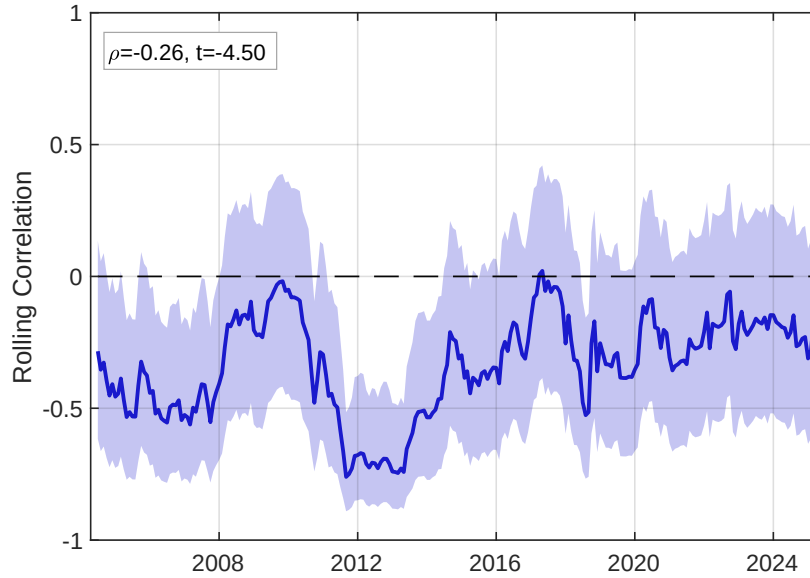


Figure 6. Flight to Safety, Dash-for-Cash, and Flight Away from Safety. The figure plots the daily Corporate Duration component against the Treasury Safety Premium from August 2002 through March 2025. Colored regions classify joint stress states, and selected outer observations from the global financial crisis, March 2020, sovereign-credit events, and monetary-policy or inflation surprises are labeled.

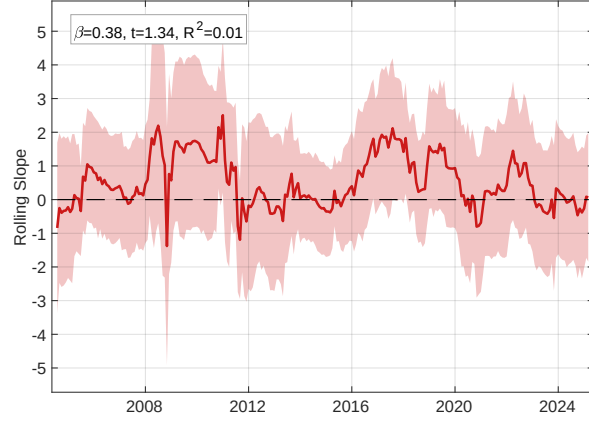


(a) Credit and Duration

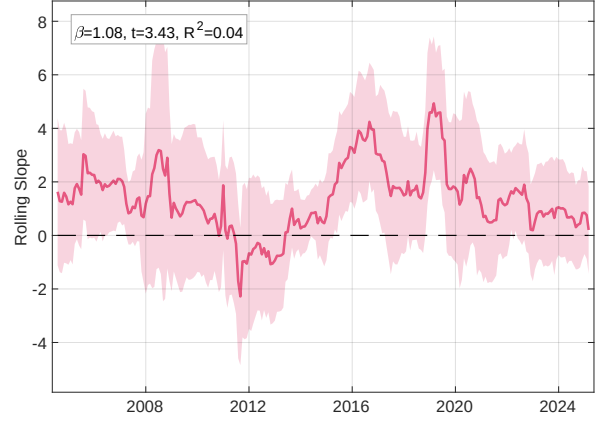


(b) Liquidity and Duration

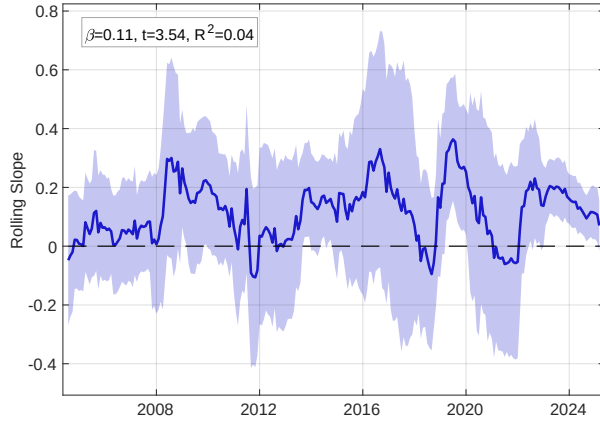
Figure 7. Credit-Spread Components and Duration. The figure plots contemporaneous correlations calculated over rolling 24-month windows between Credit and Duration in Panel A and between Liquidity and Duration in Panel B. Shaded bands show 95% confidence intervals based on the Fisher z transformation. The full-sample correlations are 0.39 and -0.26 , with t -statistics of 6.90 and -4.50 , respectively. The sample spans August 2002 through March 2025.



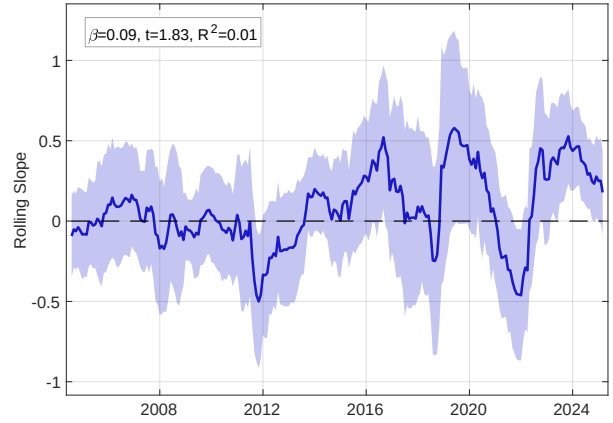
(a) Duration Predicts IG Credit



(b) Duration Predicts HY Credit

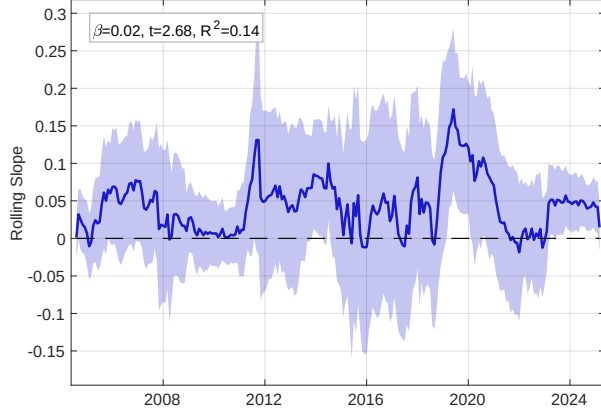


(c) Duration Predicts IG Liquidity

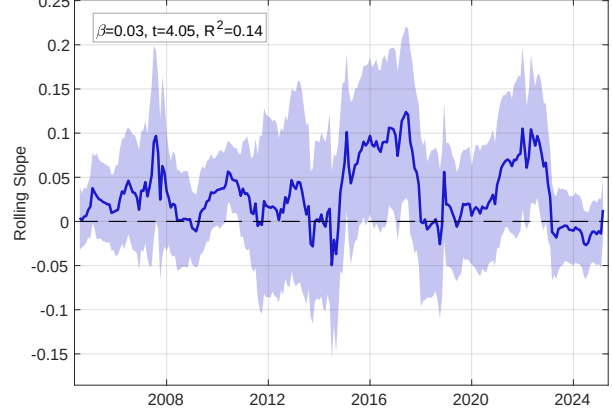


(d) Duration Predicts HY Liquidity

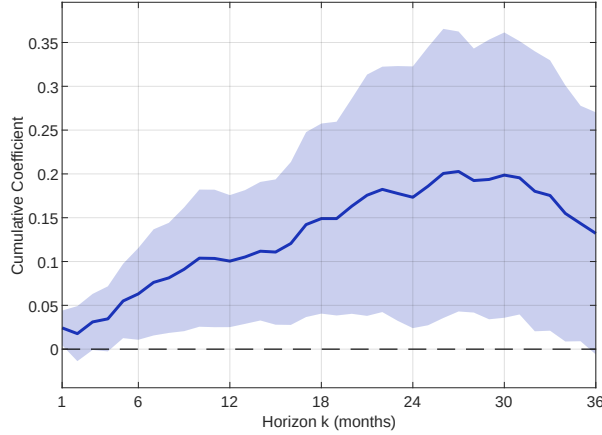
Figure 8. Duration-Driven Credit and Liquidity Risk. Each panel estimates $Y_{t+1} = a + \beta R_t^{Duration} + \epsilon_{t+1}$ and plots slope estimates calculated over rolling 24-month windows, with 95% confidence intervals. Panels A and B use Credit factors estimated from investment-grade and high-yield bonds; Panels C and D use the corresponding Liquidity factors. Text boxes report the full-sample slope, t -statistic, and predictive R^2 .



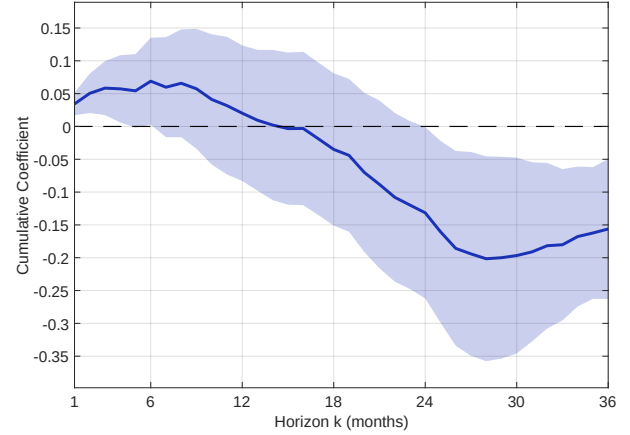
(a) IG Credit Predicts Liquidity



(b) HY Credit Predicts Liquidity



(c) Cumulative Response to IG Credit



(d) Cumulative Response to HY Credit

Figure 9. Credit-Driven Liquidity Risk. The top panels plot coefficients calculated over rolling 24-month windows from the joint regression of next month's aggregate Liquidity return on current investment-grade and high-yield Credit returns. At each horizon $k \geq 1$, the bottom panels report $\beta_{IG}(k)$ and $\beta_{HY}(k)$ from $\sum_{j=1}^k R_{t+j}^{Liquidity} = a_k + \beta_{IG}(k)R_t^{IG\,Credit} + \beta_{HY}(k)R_t^{HY\,Credit} + \epsilon_{t,k}$. Shaded bands are 95% Newey–West confidence intervals computed with $k + 1$ lags. The full-sample one-month coefficients are 0.02 and 0.03, with t -statistics of 2.68 and 4.05; the joint regression has an R^2 of 0.14.

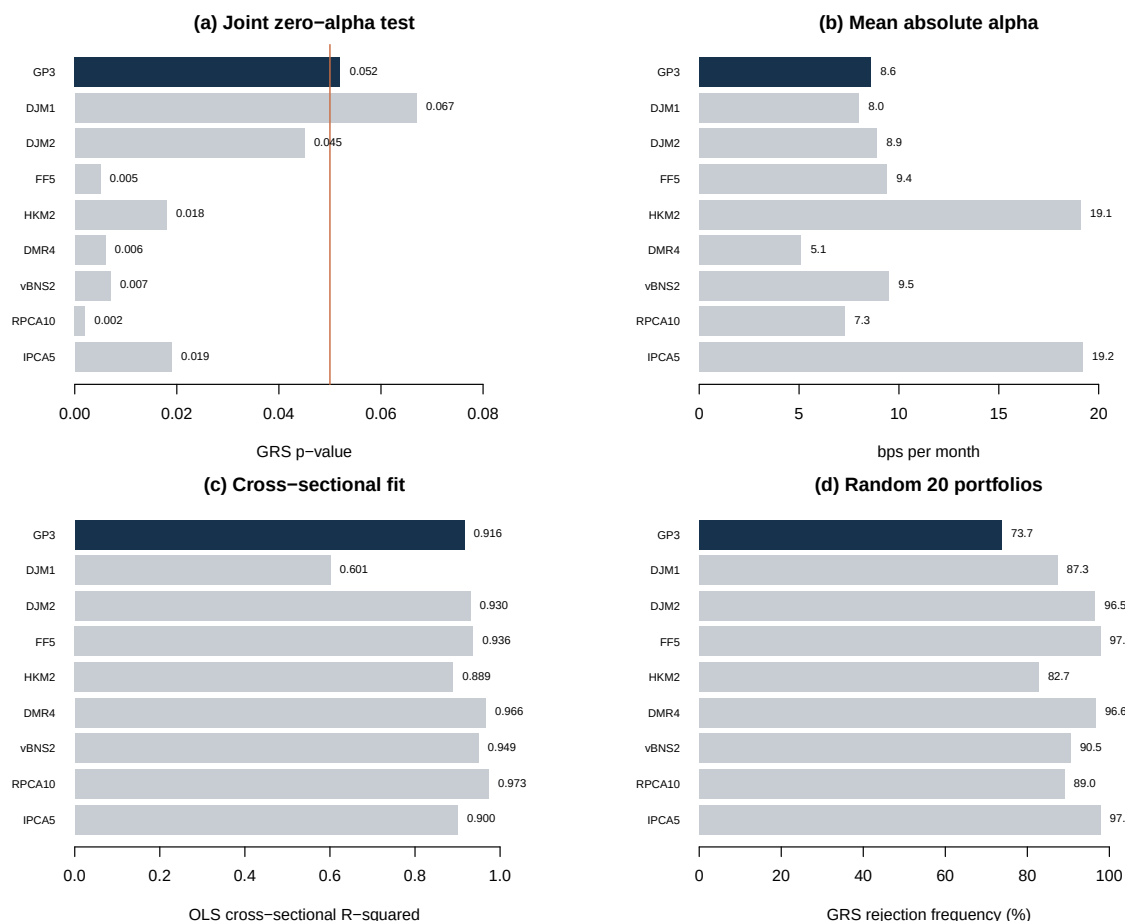


Figure 10. Pricing Performance on Corporate Bond Portfolios. Panels A, B, and C report the GRS joint-alpha p -value, mean absolute monthly alpha, and OLS cross-section R^2 for the 50 common corporate bond portfolios. Panel D reports GRS rejection frequencies across 10,000 common random selections of 20 portfolios from the broader universe of 108 corporate bond strategies. Table VII reports the exact sample ranges. The vertical line in Panel A marks the 5% significance level.

Table I
Summary Statistics

This table reports summary statistics for the bond-month estimation sample from August 2002 through March 2025. BondRet is the WRDS month-end bond return. YieldSpread is the corporate bond yield minus the maturity-matched Treasury yield. BondBeta is estimated from a rolling bond-market CAPM. Maturity and Age are measured in years. Rating maps Moody’s ratings from 1 for Aaa to 21 for C. Amount is the par amount outstanding in billions of dollars. Gamma is the negative covariance of adjacent log-price changes estimated as in [Bao, Pan, and Wang \(2011\)](#). TurnoverM is monthly par trading volume divided by lagged amount outstanding. EquityBeta is estimated from a stock-market CAPM over the preceding 60 months. EquityVolatility is annualized equity volatility estimated from up to 60 preceding monthly returns. BM, Leverage, and AssetGrowth are constructed from fiscal-year-end Compustat information. b_i^V , $-b_i^r$, and $-b_i^\xi$ denote the credit, duration, and liquidity loadings.

Variable	Mean	StdDev	Min	P25	Median	P75	Max
Panel A: Bond-Level Variables							
NumBonds	23,520						
BondRet (%)	0.40	2.55	-8.51	-0.51	0.34	1.37	9.69
YieldSpread (%)	1.80	1.96	0.05	0.71	1.19	2.10	12.58
BondBeta	1.01	0.71	-0.05	0.48	0.85	1.38	3.76
Maturity (yr)	9.26	8.41	1.10	3.47	6.13	9.89	31.11
Rating	8.15	3.05	1.00	6.00	8.00	10.00	17.00
Age (yr)	4.49	4.27	0.20	1.58	3.32	5.99	23.02
Coupon (%)	4.83	1.87	1.00	3.40	4.75	6.13	9.63
Amount (\$bn)	0.81	0.63	0.06	0.40	0.60	1.00	3.50
Gamma	0.68	1.88	-0.59	0.03	0.13	0.52	17.10
TurnoverM (%)	7.88	8.88	0.33	2.47	5.00	9.66	53.07
Call	0.86	0.35	0.00	1.00	1.00	1.00	1.00
Panel B: Equity-Level Variables							
NumIssuers	1,966						
EquitySize (log)	23.93	1.64	19.16	22.93	24.12	25.10	27.34
EquityBeta	1.07	0.57	0.14	0.63	1.01	1.40	2.56
BM	0.54	0.47	-0.30	0.23	0.45	0.73	2.50
EquityVolatility	0.30	0.18	0.11	0.19	0.25	0.35	1.19
Leverage	0.36	0.18	0.03	0.23	0.35	0.47	0.94
AssetGrowth	0.08	0.11	-0.14	0.01	0.06	0.12	0.54
Panel C: Estimated Factor Loadings							
b_i^V	0.12	0.28	0.00	0.00	0.01	0.08	1.39
$-b_i^r$	5.13	3.36	0.49	2.55	4.28	6.67	13.83
$-b_i^\xi$	1.30	1.42	0.00	0.36	0.86	1.72	7.71

Table II
Factor Returns

The table reports average factor returns under the model-driven and [Fama and French \(2020\)](#) cross-sectional normalizations. Monthly returns are in percent and daily returns are in bps; both samples span August 2002 through March 2025. For the Fama–French normalization, returns are demeaned, each predetermined loading is standardized within the cross-section, and the slopes are estimated jointly. Corr is the time-series correlation between the factor returns obtained under the two normalizations. Square brackets contain t -statistics for the average returns. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Factor	Monthly (%)			Daily (bps)		
	Model-Based	FF (2020)	Corr	Model-Based	FF (2020)	Corr
Credit	0.298*** [3.36]	0.100*** [3.55]	0.970	1.146*** [3.06]	0.420*** [3.74]	0.967
Liquidity	0.054*** [4.64]	0.076*** [4.27]	0.938	0.289*** [4.69]	0.386*** [4.64]	0.928
Duration	0.012 [0.73]	0.032 [0.59]	0.988	0.084 [1.04]	0.212 [0.83]	0.988

Table III
Macro Drivers of the Three Factors

This table reports time-series regressions of standardized monthly factor returns on standardized changes in the CBOE VIX, the MOVE index, the Treasury noise measure of [Hu, Pan, and Wang \(2013\)](#), and the 12-month-ahead financial, macroeconomic, and real uncertainty indices of [Jurado, Ludvigson, and Ng \(2015\)](#). Each coefficient measures the standard-deviation change in the factor associated with a one-standard-deviation change in the explanatory variable. The factor sample spans August 2002 through March 2025. Each specification contains 272 months. Square brackets contain t -statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Credit		Liquidity		Duration	
VIX	-0.53*** [-9.66]	-0.38*** [-5.71]		-0.18** [-2.37]		-0.12 [-1.49]
MOVE		-0.14** [-2.22]		0.04 [0.66]	-0.30*** [-4.30]	-0.23*** [-2.94]
Treasury noise		0.02 [0.29]		0.01 [0.11]		-0.04 [-0.50]
Financial uncertainty		-0.21** [-2.54]	-0.41*** [-6.92]	-0.25*** [-3.10]		-0.04 [-0.55]
Macro uncertainty		-0.01 [-0.07]		-0.24* [-1.75]		0.08 [0.49]
Real uncertainty		-0.01 [-0.08]		0.09 [0.71]		-0.05 [-0.34]
Obs	272	272	272	272	272	272
Adjusted R^2	0.28	0.32	0.17	0.20	0.08	0.08

Table IV
Market Excess-Return Regressions

This table reports time-series regressions for aggregate market excess returns. All dependent variables are monthly returns in percent in excess of the one-month Treasury bill rate. U.S. Treasury, IG, and HY use the Bloomberg U.S. Treasury Index, Bloomberg U.S. Corporate Investment Grade Index, and Bloomberg U.S. Corporate High Yield Index, respectively. Sovereign EM and Sovereign EU use the Bloomberg Emerging Markets USD Sovereign Index and Bloomberg Pan-European Aggregate Treasury Index, respectively. U.S. and foreign CorpBond are lagged-amount-weighted portfolios of bonds issued by U.S. and non-U.S. firms, respectively; Stock is the CRSP value-weighted market excess return from Kenneth French's website. The sample spans August 2002 through March 2025, except that the Sovereign EM sample begins in March 2003. Square brackets contain t -statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	U.S.					Foreign		
	CorpBond	HY	IG	Stock	Treasury	CorpBond	Sovereign EM	Sovereign EU
Panel A: Raw Excess Monthly Return (%)								
Mean	0.35*** [3.07]	0.53*** [3.41]	0.26** [2.31]	0.82*** [3.05]	0.12 [1.46]	0.41*** [3.56]	0.43*** [2.69]	0.13 [1.51]
Panel B: Duration Factor Model								
α	0.29*** [3.85]	0.49*** [3.31]	0.19*** [3.08]	0.77*** [2.94]	0.07 [1.39]	0.35*** [4.31]	0.37*** [2.89]	0.09 [1.34]
Duration	5.16*** [13.87]	2.99*** [3.90]	5.64*** [20.41]	3.49*** [2.98]	3.73*** [18.23]	4.93*** [13.49]	5.76*** [9.55]	3.24*** [13.24]
Obs	272	272	272	272	272	272	265	272
R^2	0.59	0.11	0.71	0.05	0.59	0.53	0.38	0.43
Panel C: Duration and Credit Factor Model								
α	0.15** [2.26]	0.14 [1.24]	0.12* [1.83]	0.17 [0.87]	0.17*** [3.57]	0.19*** [2.69]	0.17 [1.36]	0.12* [1.81]
Duration	4.15*** [12.35]	0.38 [0.58]	5.10*** [20.06]	-0.96 [-1.03]	4.44*** [22.95]	3.79*** [12.03]	4.11*** [7.72]	3.49*** [14.34]
Credit	0.50*** [8.40]	1.29*** [14.01]	0.27*** [4.46]	2.20*** [13.16]	-0.35*** [-9.36]	0.57*** [8.81]	0.80*** [7.73]	-0.13*** [-2.62]
Obs	272	272	272	272	272	272	265	272
R^2	0.72	0.56	0.75	0.50	0.71	0.69	0.54	0.45
Panel D: Three-Factor Model								
α	0.09 [1.37]	0.07 [0.58]	0.06 [0.88]	0.08 [0.37]	0.16*** [3.15]	0.11 [1.54]	0.11 [0.77]	0.10 [1.46]
Duration	4.91*** [11.59]	1.35 [1.56]	5.87*** [17.33]	0.31 [0.26]	4.51*** [16.39]	4.84*** [11.87]	4.95*** [6.79]	3.79*** [12.45]
Credit	0.30*** [4.13]	1.04*** [9.02]	0.07 [1.00]	1.86*** [7.82]	-0.37*** [-6.63]	0.29*** [3.91]	0.58*** [4.78]	-0.20*** [-2.89]
Liquidity	2.00*** [3.73]	2.52*** [2.73]	2.01*** [3.71]	3.33** [2.06]	0.18 [0.41]	2.75*** [4.67]	2.12** [2.05]	0.76 [1.48]
Obs	272	272	272	272	272	272	265	272
R^2	0.74	0.58	0.77	0.51	0.71	0.73	0.55	0.45

Table V
Corporate Bond Portfolio Regressions

This table reports average excess returns and three-factor regressions for value-weighted corporate bond portfolios. Each month, bonds are assigned to quintiles using information available at the preceding month-end. Returns are weighted by lagged amount outstanding and are reported in percent in excess of the one-month Treasury bill rate. Panels A–F sort bonds on lagged yield spread, credit rating, Bond CAPM beta, bond duration, the γ illiquidity measure, and bond-return volatility, respectively. Bond CAPM betas are estimated from rolling 24-month regressions with at least 10 observations. Bond-return volatility is the standard deviation of monthly bond returns over the preceding 24 months, also requiring at least 10 observations. The sample spans June 2003 through March 2025. The final three rows of each panel report the average model-based factor loadings within each portfolio. Square brackets contain t -statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

	Panel A: Yield Spread-Sorted Portfolio					Panel B: Rating-Sorted Portfolio					Panel C: Bond Beta-Sorted Portfolio				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
	Raw Excess Monthly Return					Raw Excess Monthly Return					Raw Excess Monthly Return				
Mean	0.13* [1.75]	0.21* [1.82]	0.27** [2.08]	0.35** [2.43]	0.55** [2.54]	0.19* [1.72]	0.22* [1.88]	0.27** [2.14]	0.36*** [2.65]	0.46*** [2.59]	0.14** [2.34]	0.20** [2.58]	0.26** [2.39]	0.33** [2.17]	0.46** [2.32]
	Three-Factor Model					Three-Factor Model					Three-Factor Model				
α	0.07 [1.42]	0.09 [1.48]	0.11 [1.62]	0.07 [0.71]	-0.08 [-0.48]	0.10** [2.14]	0.07 [1.22]	0.05 [0.70]	0.04 [0.42]	-0.03 [-0.22]	0.01 [0.19]	0.06 [1.03]	0.07 [0.93]	0.05 [0.58]	0.06 [0.53]
Duration	3.87*** [9.72]	6.08*** [13.19]	6.78*** [14.47]	5.51*** [7.40]	2.56** [2.22]	6.21*** [17.05]	6.17*** [14.86]	6.18*** [13.80]	4.20*** [5.47]	1.35 [1.36]	1.84*** [5.54]	3.17*** [8.65]	4.88*** [9.04]	6.95*** [10.64]	7.34*** [6.74]
Credit	-0.13** [-1.97]	-0.08 [-1.25]	0.08 [1.11]	0.44*** [4.24]	1.35*** [7.88]	-0.10 [-1.62]	0.01 [0.12]	0.10 [1.58]	0.48*** [4.43]	1.20*** [8.60]	0.09* [1.92]	0.07 [1.24]	0.12* [1.76]	0.24*** [2.80]	0.75*** [4.25]
Liquidity	1.20*** [3.01]	1.60*** [3.55]	1.60*** [2.97]	2.25*** [2.75]	4.94*** [3.69]	1.14*** [2.97]	1.69*** [3.52]	2.54*** [4.66]	2.99*** [3.36]	3.20*** [3.23]	1.65*** [3.80]	1.67*** [3.59]	2.22*** [3.93]	2.86*** [3.85]	2.80*** [2.70]
R^2	0.63	0.77	0.82	0.68	0.63	0.84	0.81	0.77	0.60	0.61	0.44	0.58	0.65	0.75	0.72
	Model-Based Factor Loadings					Model-Based Factor Loadings					Model-Based Factor Loadings				
Duration ($-b_i^r$)	3.743	5.734	6.907	6.333	4.405	5.921	5.916	5.748	4.888	3.520	2.430	3.613	4.970	6.628	8.307
Credit (b_i^V)	0.019	0.037	0.064	0.152	0.419	0.015	0.054	0.070	0.163	0.417	0.086	0.076	0.091	0.120	0.202
Liquidity ($-b_i^L$)	0.906	1.253	1.443	1.643	2.054	1.182	1.263	1.421	1.560	1.754	0.909	1.080	1.337	1.609	1.905

Table V—Continued
Corporate Bond Portfolio Regressions

	Panel D: Duration-Sorted Portfolio					Panel E: Illiquidity-Sorted Portfolio					Panel F: Bond Volatility-Sorted Portfolio				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
	Raw Excess Monthly Return					Raw Excess Monthly Return					Raw Excess Monthly Return				
Mean	0.19*** [3.36]	0.27*** [2.89]	0.31** [2.53]	0.35** [2.33]	0.30 [1.53]	0.23* [1.91]	0.23*** [2.63]	0.26** [2.39]	0.34** [2.46]	0.41** [2.40]	0.12*** [2.69]	0.22*** [2.66]	0.27** [2.24]	0.34** [2.08]	0.48*** [2.27]
	Three-Factor Model					Three-Factor Model					Three-Factor Model				
α	0.06 [1.15]	0.05 [0.62]	0.05 [0.55]	0.06 [0.66]	0.03 [0.48]	0.03 [0.32]	0.10 [1.64]	0.08 [1.14]	0.07 [0.86]	-0.05 [-0.49]	0.06 [1.60]	0.10* [1.70]	0.07 [0.87]	0.07 [0.76]	-0.06 [-0.48]
Duration	0.93*** [2.81]	2.16*** [4.18]	3.65*** [5.51]	6.91*** [11.20]	10.56*** [18.49]	4.42*** [6.15]	3.83*** [9.95]	4.90*** [10.90]	6.26*** [12.20]	6.58*** [9.12]	1.89*** [7.29]	3.98*** [10.43]	5.45*** [9.35]	7.65*** [11.18]	6.10*** [5.55]
Credit	0.19*** [3.28]	0.38*** [4.34]	0.42*** [4.29]	0.21** [2.10]	0.19** [2.56]	0.34*** [3.41]	0.10* [1.79]	0.19*** [2.69]	0.31*** [3.79]	0.50*** [4.36]	-0.04 [-0.80]	-0.00 [-0.07]	0.16** [2.32]	0.29*** [3.44]	1.05*** [6.04]
Liquidity	1.39*** [3.42]	2.02*** [3.37]	2.17*** [3.07]	3.20*** [4.08]	2.36*** [4.24]	1.52*** [2.08]	1.33*** [3.16]	1.70*** [3.17]	2.67*** [4.18]	5.21*** [5.61]	0.97*** [3.06]	1.65*** [3.52]	2.11*** [3.34]	2.40*** [3.47]	4.16*** [3.74]
R^2	0.38	0.52	0.56	0.75	0.90	0.58	0.66	0.74	0.78	0.75	0.43	0.63	0.67	0.78	0.71
	Model-Based Factor Loadings					Model-Based Factor Loadings					Model-Based Factor Loadings				
Duration ($-b_i^V$)	1.800	3.136	4.524	6.550	10.489	4.734	4.280	5.319	6.410	6.941	2.518	4.335	5.678	7.928	7.275
Credit (b_i^V)	0.114	0.154	0.146	0.095	0.074	0.111	0.084	0.098	0.131	0.210	0.036	0.068	0.097	0.130	0.308
Liquidity ($-b_i^S$)	0.791	1.178	1.396	1.626	1.938	0.218	0.714	1.275	2.067	3.702	0.743	1.178	1.463	1.769	2.139

Table VI
Decomposing Treasury Returns

This table reports time-series regressions of monthly excess returns on the Treasury duration component, the corporate bond duration component, and their difference, which we call the Safety Premium. The independently estimated duration components span August 2002 through March 2025. Panels A through D consider aggregate equity, Treasury, investment-grade corporate bond, and high-yield corporate bond returns. Panels E and F use the Credit and Liquidity factors. All dependent variables are in percent except the Liquidity factor in Panel F, which is in basis points. Reported in square brackets are t -statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Stock				Panel B: Treasury			
USTDuration	-0.02 [-1.24]				0.05*** [28.65]			
CorpDuration	0.04*** [3.64]				0.04*** [16.32]			
Safety	-0.16*** [-8.08]				0.01** [2.47]			
Constant	0.85*** [3.13]	0.75*** [2.86]	0.83*** [3.92]	0.83*** [3.82]	0.03 [1.05]	0.06 [1.08]	0.12 [1.46]	0.03 [1.05]
Obs	272	272	272	272	272	272	272	272
R^2	0.01	0.07	0.37	0.37	0.85	0.55	0.03	0.85
	Panel C: IG				Panel D: HY			
USTDuration	0.05*** [9.09]				-0.00 [-0.20]			
CorpDuration	0.06*** [20.47]				0.03*** [4.45]			
Safety	-0.05*** [-6.12]				-0.10*** [-8.22]			
Constant	0.18** [2.03]	0.17*** [2.74]	0.27*** [2.68]	0.17*** [2.98]	0.54*** [3.39]	0.47*** [3.21]	0.54*** [4.69]	0.53*** [4.48]
Obs	272	272	272	272	272	272	272	272
R^2	0.39	0.73	0.22	0.74	0.00	0.14	0.45	0.46
	Panel E: Credit Factor				Panel F: Liquidity Factor			
USTDuration	0.00 [0.59]				-0.33*** [-7.89]			
CorpDuration	0.02*** [8.63]				-0.15*** [-4.01]			
Safety	-0.06*** [-13.41]				-0.36*** [-5.09]			
Constant	0.29*** [3.32]	0.26*** [3.26]	0.30*** [4.63]	0.29*** [4.48]	5.99*** [5.72]	5.66*** [4.96]	5.45*** [4.91]	5.97*** [5.89]
Obs	272	272	272	272	272	272	272	272
R^2	0.00	0.19	0.45	0.48	0.19	0.05	0.10	0.25

Table VII
Model Comparison on Corporate Bond Portfolios

Panel A evaluates each model on the same 50 corporate bond portfolios and reports the GRS joint-alpha p -value, mean absolute alpha in bps per month, and OLS and GLS cross-sectional R^2 . Panel B uses 10,000 common random selections of 20 portfolios from the 108 corporate bond strategies. Each model is evaluated over its longest sample shared with the corresponding test assets. The complete 108-portfolio universe begins in August 2003. The paper abbreviations refer to this paper; [Dickerson, Julliard, and Mueller \(2023\)](#); [Fama and French \(1993\)](#); [He, Kelly, and Manela \(2017\)](#); [Bai, Bali, and Wen \(2019\)](#), using the corrected series of [Dickerson, Mueller, and Robotti \(2023\)](#); [van Binsbergen, Nozawa, and Schwert \(2025\)](#); [Chen et al. \(2026\)](#); and [Kelly, Palhares, and Pruitt \(2023\)](#). RPCA10 uses the specification with $a \neq 0$, and IPCA5 imposes $\Gamma_\alpha = 0$.

Panel A: Pricing 50 Corporate Bond Portfolios								
Paper	Model	Begin	End	T	GRS p	$ \alpha $ (bps)	OLS R^2	GLS R^2
This paper	GP3	2002:08	2022:12	245	0.052	8.6	0.916	0.091
DJM (2023)	DJM1	2002:08	2022:12	245	0.067	8.0	0.601	0.070
DJM (2023)	DJM2	2002:08	2022:12	245	0.045	8.9	0.930	0.070
FF (1993)	FF5	2002:08	2022:12	245	0.005	9.4	0.936	0.079
HKM (2017)	HKM2	2002:08	2022:12	245	0.018	19.1	0.889	0.022
DMR (2023)	DMR4	2004:08	2021:12	209	0.006	5.1	0.966	0.155
vBNS (2025)	vBNS2	2002:08	2020:12	221	0.007	9.5	0.949	0.124
CRWZ (2026)	RPCA10	2004:07	2021:12	210	0.002	7.3	0.973	0.205
KPP (2023)	IPCA5	2003:08	2020:09	206	0.019	19.2	0.900	0.198
Panel B: Random 20 Portfolios								
Paper	Model	Begin	End	T	GRS Reject (%)	Mean GRS p	Mean R_{OLS}^2 (SD)	Mean R_{GLS}^2 (SD)
This paper	GP3	2003:08	2022:12	233	73.7	0.046	0.593 (0.146)	0.175 (0.064)
DJM (2023)	DJM1	2003:08	2022:12	233	87.3	0.023	0.466 (0.150)	0.063 (0.034)
DJM (2023)	DJM2	2003:08	2022:12	233	96.5	0.008	0.538 (0.148)	0.097 (0.040)
FF (1993)	FF5	2003:08	2022:12	233	97.8	0.006	0.686 (0.127)	0.316 (0.112)
HKM (2017)	HKM2	2003:08	2022:12	233	82.7	0.031	0.548 (0.154)	0.098 (0.054)
DMR (2023)	DMR4	2004:08	2021:12	209	96.6	0.007	0.677 (0.120)	0.222 (0.064)
vBNS (2025)	vBNS2	2003:08	2020:12	209	90.5	0.018	0.565 (0.151)	0.127 (0.055)
CRWZ (2026)	RPCA10	2004:07	2021:12	210	89.0	0.020	0.852 (0.083)	0.440 (0.133)
KPP (2023)	IPCA5	2003:08	2020:09	206	97.8	0.008	0.756 (0.107)	0.438 (0.108)

Table VIII
Sharpe Ratios and Incremental Investment Opportunities

Each row compares GP3 with a benchmark over their longest common factor sample. Max SR is the annualized ex-post maximum Sharpe ratio computed from the reported factor-return vector as $\sqrt{12 \boldsymbol{\mu}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}}$. Adj. SR applies the finite-sample correction of Barillas, Kan, Robotti, and Shanken (2020). Nested GRS p tests whether the three GP factors have jointly zero alpha relative to the benchmark. $\Delta \text{SR}^2 p$ is the two-sided p -value from a centered circular block bootstrap with 12-month blocks and 10,000 draws. The paper abbreviations are defined in Table VII.

Paper	Model	Begin	End	T	GP3		Benchmark		Nested GRS p	$\Delta \text{SR}^2 p$
					Max SR	Adj. SR	Max SR	Adj. SR		
DJM (2023)	DJM1	2002:08	2022:12	245	1.084	1.002	0.613	0.567	0.001	0.330
DJM (2023)	DJM2	2002:08	2022:12	245	1.084	1.002	0.616	0.525	< 0.001	0.314
FF (1993)	FF5	2002:08	2022:12	245	1.084	1.002	0.763	0.566	< 0.001	0.351
HKM (2017)	HKM2	2002:08	2022:12	245	1.084	1.002	0.661	0.576	0.001	0.363
DMR (2023)	DMR4	2004:08	2021:12	209	1.216	1.128	0.994	0.854	0.004	0.505
vBNS (2025)	vBNS2	2002:08	2020:12	221	1.115	1.026	0.999	0.934	< 0.001	0.798
CRWZ (2026)	RPCA10	2004:07	2021:12	210	1.217	1.129	1.268	0.972	< 0.001	0.702
KPP (2023)	IPCA5	2003:08	2020:09	206	1.063	0.964	8.185	8.027	0.004	< 0.001

Table IX
Two-Way Factor Spanning Tests

Panel A regresses the baseline GP factors on each benchmark and reports the joint GRS test followed by monthly intercepts in percent with six-lag Newey–West t -statistics. Panel B reverses the regressions. Sig./ K is the number of individual benchmark intercepts with $|t| > 1.96$ relative to the number of benchmark factors. Each row uses the longest common factor sample, and the paper abbreviations are defined in Table VII.

Panel A: GP3 Factors on Each Benchmark								
Paper	Model	Begin	End	T	GRS p	Credit α [t]	Duration α [t]	Liquidity α [t]
DJM (2023)	DJM1	2002:08	2022:12	245	0.001	0.15 [1.78]	-0.02 [-1.47]	0.05 [2.76]
DJM (2023)	DJM2	2002:08	2022:12	245	< 0.001	0.16 [2.15]	-0.02 [-2.98]	0.05 [3.70]
FF (1993)	FF5	2002:08	2022:12	245	< 0.001	0.11 [1.44]	-0.02 [-4.15]	0.05 [3.36]
HKM (2017)	HKM2	2002:08	2022:12	245	0.001	0.12 [1.55]	0.00 [0.22]	0.04 [2.65]
DMR (2023)	DMR4	2004:08	2021:12	209	0.004	0.09 [1.54]	0.00 [-0.47]	0.04 [2.77]
vBNS (2025)	vBNS2	2002:08	2020:12	221	< 0.001	0.17 [2.05]	-0.03 [-3.18]	0.05 [3.47]
CRWZ (2026)	RPCA10	2004:07	2021:12	210	< 0.001	0.05 [0.84]	-0.01 [-1.21]	0.05 [3.55]
KPP (2023)	IPCA5	2003:08	2020:09	206	0.004	-0.31 [-2.23]	0.07 [1.61]	-0.06 [-2.22]
Panel B: Benchmark Factors on GP3								
Paper	Model	Begin	End	T	GRS p	Sig./ K	Max factor	α [t]
DJM (2023)	DJM1	2002:08	2022:12	245	0.373	0/1	MKTB	0.06 [0.70]
DJM (2023)	DJM2	2002:08	2022:12	245	0.001	1/2	TERM	0.42 [3.60]
FF (1993)	FF5	2002:08	2022:12	245	0.005	1/5	TERM	0.42 [3.60]
HKM (2017)	HKM2	2002:08	2022:12	245	0.235	0/2	CPTLT	-0.39 [-1.04]
DMR (2023)	DMR4	2004:08	2021:12	209	0.237	0/4	LRF	0.11 [1.31]
vBNS (2025)	vBNS2	2002:08	2020:12	221	< 0.001	1/2	Bond dur.	0.28 [4.12]
CRWZ (2026)	RPCA10	2004:07	2021:12	210	0.013	2/10	RPCA10	0.98 [3.24]
KPP (2023)	IPCA5	2003:08	2020:09	206	< 0.001	3/5	IPCA1	4.22 [11.93]

Internet Appendix for Model-Based Cross-Section Factors in Corporate Bonds

ZHE GENG and JUN PAN*

This Internet Appendix provides the technical derivations supporting the main text.

I Technical Proofs

Throughout, $\tau = T - t$ and expectations are taken under the risk-neutral measure Q conditional on time- t information.

Proof of Lemma 1

Let

$$\Lambda_{t,T} = \int_t^T (r_s + l_i \xi_s) ds.$$

Because r_s and ξ_s are jointly Gaussian Ornstein–Uhlenbeck processes, $\Lambda_{t,T}$ is conditionally Gaussian. Hence

$$R(r_t, \xi_t, \tau) = \mathbb{E}_t^Q[e^{-\Lambda_{t,T}}] = \exp\left\{-\mathbb{E}_t^Q[\Lambda_{t,T}] + \frac{1}{2} \text{Var}_t^Q(\Lambda_{t,T})\right\}. \quad (\text{IA.1})$$

The conditional means of the integrated state variables are

$$\begin{aligned} \mathbb{E}_t^Q\left[\int_t^T r_s ds\right] &= \frac{\alpha_r}{\kappa_r} \tau + \frac{1 - e^{-\kappa_r \tau}}{\kappa_r} \left(r_t - \frac{\alpha_r}{\kappa_r}\right), \\ \mathbb{E}_t^Q\left[\int_t^T \xi_s ds\right] &= \frac{\alpha_\xi}{\kappa_\xi} \tau + \frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi} \left(\xi_t - \frac{\alpha_\xi}{\kappa_\xi}\right). \end{aligned}$$

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Thus, the coefficients on r_t and ξ_t in $-\mathbb{E}_t^Q[\Lambda_{t,T}]$ are $B(\tau)$ and $C_i(\tau)$ in equation (10). Moreover,

$$\text{Var}_t^Q(\Lambda_{t,T}) = \omega_{rr}(\tau) + l_i^2 \omega_{\xi\xi}(\tau) + 2l_i \omega_{r\xi}(\tau).$$

Evaluating the three integrated covariance terms gives equation (12); collecting the state-independent terms in equation (IA.1) gives $A_i(\tau)$ in equation (11). $\blacksquare$

Proof of Proposition 1

Following the contingent-claim argument of Longstaff and Schwartz (1995), write the terminal payoff as

$$\min(V_T^i, K) = K - (K - V_T^i) \mathbb{I}_{\{V_T^i \leq K\}}.$$

Equation (7) then becomes

$$\begin{aligned} P_t^i &= KR(r_t, \xi_t, \tau) - K \mathbb{E}_t^Q \left[e^{-\Lambda_{t,T}} \mathbb{I}_{\{V_T^i \leq K\}} \right] \\ &\quad + \mathbb{E}_t^Q \left[e^{-\Lambda_{t,T}} V_T^i \mathbb{I}_{\{V_T^i \leq K\}} \right]. \end{aligned} \quad (\text{IA.2})$$

Second term. Let $H(V_t^i, r_t, \xi_t, t)$ denote the price of a contingent claim paying $\mathbb{I}_{\{V_T^i \leq K\}}$ at T , and write $H = RQ$, where $R = R(r_t, \xi_t, \tau)$ is given by Lemma 1. With $X \equiv V_t^i/K$, substituting $H = RQ$ into the pricing equation (8) gives

$$\begin{aligned} &\frac{\sigma^2}{2} X^2 Q_{XX} + \frac{\eta_r^2}{2} Q_{rr} + \frac{\eta_\xi^2}{2} Q_{\xi\xi} + \beta_i \sigma_V \eta_r \rho_{Vr} X Q_{Xr} + \beta_i \sigma_V \eta_\xi \rho_{V\xi} X Q_{X\xi} + \rho_{r\xi} \eta_r \eta_\xi Q_{r\xi} \\ &\quad + [r + \beta_i \sigma_V \eta_r \rho_{Vr} B(\tau) + \beta_i \sigma_V \eta_\xi \rho_{V\xi} C_i(\tau)] X Q_X \\ &\quad + [\alpha_r - \kappa_r r + \eta_r^2 B(\tau) + \rho_{r\xi} \eta_r \eta_\xi C_i(\tau)] Q_r \\ &\quad + [\alpha_\xi - \kappa_\xi \xi + \eta_\xi^2 C_i(\tau) + \rho_{r\xi} \eta_r \eta_\xi B(\tau)] Q_\xi = -Q_t, \end{aligned} \quad (\text{IA.3})$$

with terminal condition $Q(X, r, \xi, T) = \mathbb{I}_{\{X \leq 1\}}$. The substitution cancels the discount-rate term $-(r + l_i \xi)H$. The terms involving $B(\tau)$ and $C_i(\tau)$ are the drift adjustments induced

by using R as numeraire.

Under these shifted dynamics, $\ln X_T$ is conditionally normal with mean $\ln X_t + M_i(r_t, \tau)$ and variance $S_i^2(\tau)$. Evaluating the shifted drifts and conditional variance gives equations (14)–(15). In particular, the liquidity adjustment to the conditional mean is

$$\Delta M_i^{\text{liq}} = -l_i \left[\omega_{r\xi}(\tau) + \frac{\beta_i \sigma_V \eta_\xi \rho_{V\xi}}{\kappa_\xi} \left(\tau - \frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi} \right) \right].$$

The Girsanov adjustment changes the drift but not the diffusion covariance matrix. Consequently, $S_i^2(\tau)$ is the same as in the no-liquidity case: liquidity affects the conditional mean through its covariance with the discount factor but does not add a separate diffusion term to firm value. It follows that

$$K \mathbb{E}_t^Q \left[e^{-\Lambda_{t,T}} \mathbb{I}_{\{V_T^i \leq K\}} \right] = KR(r_t, \xi_t, \tau) N(-d_2), \quad (\text{IA.4})$$

where $d_2 = [\ln(V_t^i/K) + M_i(r_t, \tau)]/S_i(\tau)$.

Third term. Under the measure associated with the numeraire R , let $Y \equiv \ln X_T$. Then $Y \sim N(\mu_i, S_i^2(\tau))$, where $\mu_i = \ln X_t + M_i(r_t, \tau)$. Therefore,

$$\begin{aligned} \mathbb{E}_t^Q \left[e^{-\Lambda_{t,T}} V_T^i \mathbb{I}_{\{V_T^i \leq K\}} \right] &= KR(r_t, \xi_t, \tau) \mathbb{E}_t^{Q^R} \left[e^Y \mathbb{I}_{\{Y \leq 0\}} \right] \\ &= KR(r_t, \xi_t, \tau) e^{\mu_i + S_i^2(\tau)/2} N\left(\frac{-\mu_i - S_i^2(\tau)}{S_i(\tau)}\right) \\ &= V_t^i R(r_t, \xi_t, \tau) e^{M_i(r_t, \tau) + S_i^2(\tau)/2} N(-d_1), \end{aligned}$$

where $d_1 = d_2 + S_i(\tau)$. The second equality follows by completing the square in the truncated-normal integral,

$$\int_{-\infty}^0 e^y \frac{1}{S_i(\tau)} \phi\left(\frac{y - \mu_i}{S_i(\tau)}\right) dy = e^{\mu_i + S_i^2(\tau)/2} N\left(\frac{-\mu_i - S_i^2(\tau)}{S_i(\tau)}\right).$$

Combining the three payoff terms gives equation (13). In the first term, we use $1 -$

$$N(-d_2) = N(d_2). \quad \blacksquare$$

Proof of Proposition 2

Applying Itô's lemma to $P_t^i = P(V_t^i, r_t, \xi_t, t)$ gives

$$\begin{aligned} \frac{dP_t^i}{P_t^i} = & \frac{\mathcal{L}P_t^i + \partial P_t^i / \partial t}{P_t^i} dt + \frac{\partial \ln P_t^i}{\partial \ln V_t^i} \left(\beta_i \sigma_V dB_t^V + \sigma_i dB_t^{V,i} \right) \\ & + \frac{\partial \ln P_t^i}{\partial r_t} \eta_r dB_t^r + \frac{\partial \ln P_t^i}{\partial \xi_t} \eta_\xi dB_t^\xi, \end{aligned} \quad (\text{IA.5})$$

where $\mathcal{L}$ is the diffusion generator implied by equations (3), (5), and (6). The pricing equation (8) implies $\mathcal{L}P_t^i + \partial P_t^i / \partial t = (r_t + l_i \xi_t) P_t^i$. Substituting this identity into equation (IA.5), subtracting $r_t dt$, and separating the systematic and firm-specific asset innovations gives

$$\begin{aligned} \frac{dP_t^i}{P_t^i} - r_t dt = & \left(\beta_i \frac{\partial \ln P_t^i}{\partial \ln V_t^i} \right) \sigma_V dB_t^V + \frac{\partial \ln P_t^i}{\partial r_t} \eta_r dB_t^r \\ & + \frac{\partial \ln P_t^i}{\partial \xi_t} \eta_\xi dB_t^\xi + l_i \xi_t dt + \frac{\partial \ln P_t^i}{\partial \ln V_t^i} \sigma_i dB_t^{V,i}. \end{aligned} \quad (\text{IA.6})$$

It remains to evaluate the three derivatives. Write

$$\mathcal{D}_i = KN(d_2) + V_t^i e^{M_i(r_t, \tau) + S_i^2(\tau)/2} N(-d_1), \quad P_t^i = R \mathcal{D}_i.$$

The normal-density identity $K\phi(d_2) = V_t^i e^{M_i(r_t, \tau) + S_i^2(\tau)/2} \phi(d_1)$ implies

$$\frac{\partial \mathcal{D}_i}{\partial \ln V_t^i} = V_t^i e^{M_i(r_t, \tau) + S_i^2(\tau)/2} N(-d_1). \quad (\text{IA.7})$$

Since ξ_t enters the price through the affine discount factor,

$$\frac{\partial \ln P_t^i}{\partial \xi_t} = C_i(\tau) = -\frac{1 - e^{-\kappa_\xi \tau}}{\kappa_\xi} l_i. \quad (\text{IA.8})$$

For the short rate, differentiating the two legs of the bond price and using the same density

identity yields

$$\frac{\partial \ln P_t^i}{\partial r_t} = B(\tau) \frac{KR(r_t, \xi_t, \tau)N(d_2)}{P_t^i} = -\frac{1 - e^{-\kappa_r \tau}}{\kappa_r} \frac{KR(r_t, \xi_t, \tau)N(d_2)}{P_t^i}. \quad (\text{IA.9})$$

Combining equations (IA.7)–(IA.9) with equation (IA.6) delivers the loadings in equations (17)–(19) and the return decomposition in equation (16). ■