Constructing Model-Based Cross-Section Factors in the Corporate Bond Market

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Abstract

Using a structural model of default with stochastic interest rates and liquidity shocks, we extract three common risk factors – credit, duration, and liquidity – from the cross-section of corporate bond returns. Our estimation is unique in that, instead of bond characteristics, we use the model-implied factor loadings of bond returns on the three state variables of the model – the systematic asset value, interest rate and liquidity. Our theory-based three-factor model can explain corporate bond risk premiums in both the aggregate and cross-section. Moreover, the model-implied factors can be used to gauge the relative importance of credit, liquidity, and duration, allowing us to identify distinct episodes of flights-to-quality, flights-to-liquidity and flights-to-cash. We further demonstrate the broader implications of the factors: the credit factor explains stock and sovereign returns, the liquidity factor reflects dealers' post-regulation capacity, and the duration factor measures the convenience yield of US Treasuries.

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1 Introduction

The U.S. corporate bond market, with amount outstanding of $11.1 trillion by 2024, 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 credit, macro, and intermediation, it also contains rich information on duration, credit, and liquidity risks. Specifically, 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 is influenced by 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 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 from it the common risk factors of duration, credit, and liquidity. Central to our empirical approach is a structural model of default with stochastic interest-rate risk and Poisson-driven liquidity shock. Associated with the three state variables of the model are three risk factors – credit, liquidity, and duration, which we infer using bond-level factor loadings implied by the model.

Unlike the existing cross-sectional literature in equity and bond, which uses stock or bond characteristics to form empirically-motivated factors, our empirical approach is unique in that our risk factors emerge from an arbitrage-free asset-pricing model. Moreover, they are extracted from the cross-section of corporate bond returns using model-implied factor loadings. Intuitively, bonds of varying maturity can be informative about the pricing of the duration risk factor, while bonds of different credit/liquidity qualities can inform us about the credit/liquidity risk factors. This is exactly the essence of our estimation strategy, except that, in our model-based approach, such cross-sectional variations in duration, credit quality, and liquidity are captured by our model-implied factor loadings. Accordingly, our extracted factors offer a clean identification of credit, liquidity, and duration.

Since 2008, the corporate bond market has experienced significant shocks in credit, liquidity, and duration (e.g., 2008 financial crisis, post-2008 financial regulations, Covid-19, post-Covid inflation surge and the ensuing rate hikes). Against this backdrop, our model-implied factors can be used to gauge and differentiate the relative importance of credit, liquidity, and duration over the varying degrees of financial and macro uncertainties and intermediary constraints.[1] The extreme outcomes of our model-implied factors can further

[1]For 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

help us identify episodes of flight-to-cash or dash-for-cash when our duration factor suddenly drops. Likewise, episodes of flight-to-quality and flight-to-liquidity can be separately identified using extreme values of our credit and liquidity factors.[2] Importantly, the clean identification of our model-based factors allows us to separately locate such important and influential episodes in history. A better understanding of their nature and origin can help us gauge the effectiveness of the policies and regulations enacted at the time.

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, the time-t bond i's price $P_t^i = f(V_t, r_t, N_t)$ is a function of three state variables – V_t is the systematic component of the firm's asset value, r_t is the stochastic interest rate, and N_t is a poisson process capturing the liquidity shocks. Associated with the three state variables of the model are the three risk factors – V_t and its distance to the default boundary give rise to the credit risk (Merton, 1974), the presence of r_t introduces the duration risk (Longstaff and Schwartz, 1995), and N_t the liquidity risk (Bao et al., 2011).

An important step to our model-based extraction of risk factors is to take advantage of the model-based factor loadings. For each bond i, we use the model to compute its factor loading on credit $b_v^i = \partial \ln P_t^i / \partial \ln V_t$, driven mostly by firm's credit quality; on duration $b_r^i = \partial \ln P_t^i / \partial r_t$, linked directly to the maturity of the bond; on liquidity $b_N^i = e^{-\kappa_i} - 1$, which we use the liquidity measure of Bao et al. (2011). Following the insight of Liu et al. (2025) and assuming the existence of a risk-neutral measure, the instantaneous return of bond i in excess of the riskfree rate follows

$$\frac{dP_t^i}{P_t^i} - r_t dt = b_v^i \, dF_t^v + b_r^i \, dF_t^r + b_N^i \, dF_t^N + de_t^i \,, \tag{1}$$

where $dF^v = \sigma_v dB_t^v$, $dF^r = \eta dB_t^r$, and $dF^N = dN_t - \lambda dt$ are the latent risk factors associated with the credit risk, interest rate risk and liquidity shocks, whose means are zero under the risk-neutral measure $\mathbb{Q}$ and non-zero under the physical measure, with the factor risk

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.

[2]Prominent examples of flight-to-cash include June 20, 2013, the day after Bernanke's taper speech; March 12, 17, and 19, 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), the peak of the 2008 financial crisis (early October 2008), March 9, 2020 (Covid-19), and June 13, 2022, (CPI announcement indicating accelerating inflation). Flight-to-liquidity days captured by our liquidity factor include August 8, 2011 (the black Monday due to U.S. debt ceiling crisis), October 15, 2014 (U.S. Treasury flash crash), March 23, 2020 (announcement of Fed SMCCF to provide liquidity to corporate bonds), and March 13, 2023 (SVB bankruptcy).

premium driving the difference. Representing idiosyncratic risk, de_t^i is zero mean under both the risk-neutral and the physical measure.

Central to our model-based factor extraction is the pricing relation in Equation (1). Fixing time t, we can use the large cross-section of bond returns to extract the time-t latent factors. 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. While this empirical approach of running cross-sectional regression to extract the latent factors is similar to that of Kelly et al. (2019) and Fama and French (2020), there is an important and conceptual difference between the two. In particular, instead of using bond characteristics, we use model-implied factor loadings to extract the latent factors and, more importantly, the pricing relation in in Equation (1) is dictated by an arbitrage-free asset pricing model. This model-based factor approach differentiates our paper importantly from the existing cross-sectional studies on corporate bonds with empirically motivated factors (e.g., Fama and French (1993), Bai et al. (2019), and Dickerson et al. (2023)).

A Three-Factor Model of Credit, Liquidity, and Duration – We first examine whether our model-based three factors carry significant risk premia. Our analysis reveals that both the credit and liquidity factors carry economically and statistically significant risk premia, with these effects being particularly pronounced during the post-financial-crisis period. The credit factor averages 24 bps (t-statistics = 1.90) from 2005 to 2023, increasing substantially to 39 bps (t-statistics = 2.86) in the post-crisis era. Meantime, the liquidity factor maintains a consistent premium of 4-5 bps (t-statistics = 4.29-4.45) throughout our sample period, reflecting the persistent pricing of liquidity risk. Although the duration factor does not exhibit statistically significant risk premium, it demonstrates a strong correlation with Treasury returns, suggesting its primary importance lies in capturing systematic interest rate exposure.

Building on these baseline results, we investigate how the relative importance of credit, liquidity, and duration risks has evolved over time. Employing principal component analysis (PCA) and Shapley value decompositions, we document significant shifts in the dominant source of risk across different market regimes. Credit risk emerges as the primary driver during the 2008 financial crisis and the 2016 junk bond closure, explaining up to 95% the variation in the first principal component. Liquidity risk gains prominence after 2017, coinciding with regulatory changes that increased dealers' balance sheet costs, while duration risk takes the lead during the 2022 interest rate hike and the 2012 European debt crisis.

These patterns highlight the shifting importance of credit, liquidity, and duration risks over time.

The interaction among our three factors also reveals important cross-risk dynamics. We observe a significantly increasing correlation between credit and liquidity risks, with further analysis suggesting a pronounced credit-driven liquidity effect that becomes particularly evident after 2008. Additionally, we document a positive correlation between credit and duration factors, and a stronger negative correlation between liquidity and duration factors. These complex interrelationships reflect the interplay of flight-to-quality, flight-to-liquidity, and flight-to-cash behaviors in fixed income markets. When considering the combined effect of credit and liquidity factors on duration, the negative correlation dominates, resulting in an overall negative relationship. This finding aligns with the established negative correlation between credit spread changes and Treasury yields documented by Longstaff and Schwartz (1995).

To further understand the macro drivers of our model-based bond factors, we examine their time-series relationships with key uncertainty indicators and market variables. The credit factor demonstrates particularly strong sensitivity to the VIX index, alongside financial uncertainty measure from Jurado et al. (2015) and the MOVE index, with the VIX emerging as the strongest driver. The liquidity factor shows negative correlations with financial uncertainty index, indicating that liquidity conditions are closely tied to the financial sector's health and the balance-sheet costs faced by intermediaries. It also exhibiting a positive relationship with 10-Year Treasury yield changes. The duration factor moves closely with Treasury yield changes while showing significant negative correlation with the VIX, with the 10-Year UST yield being the most significant driver, highlighting the importance of interest rate movements in shaping duration risk.

Leveraging the unique advantages of our daily frequency estimation methodology, we extend our analysis to factor behaviors during specifically identified major macroeconomic events. On FOMC meeting days, both credit and duration factors earn economically substantial and statistically significant premia of 11.11 bps (t-statistics = 4.05) and 1.37 bps (t-statistics = 3.02) respectively, while showing no significant premia on non-FOMC days. The liquidity factor demonstrates distinctly different sensitivity patterns, showing greater significance on Nonfarm Payroll announcement days compared to other macroeconomic releases. This event-based analysis implies how each factor responds uniquely to specific macroeconomic conditions, indicating the dynamic nature of risk premia in financial markets.

The Implications of Three-Factor Model of Credit, Liquidity, and Duration – Having studied the risk premia and drivers of our three factors, we now demonstrate their broad applicability to understand asset pricing and market structure. We first evaluate the model's performance in explaining aggregate risk premia across major asset classes. Our three-factor model substantially reduces the excess monthly return of investment-grade corporate bonds from 26 bps (t-statistics=1.95) to 6 bps (t-statistics=0.77), high-yield bonds from 49 bps (t-statistics=2.47) to 16 bps (t-statistics=1.17), and the aggregate stock market from 76 bps (t-statistics=2.55) to 35 bps (t-statistics=1.62). The factors also explain significant portions of excess returns in international bond indices and emerging market sovereign debt. In Treasury markets, the positive correlation between our duration factor and Treasury returns, combined with the negative correlation between the credit factor and Treasury returns, clearly captures flight-to-safety dynamics during market stress.

Extending to cross-sectional asset pricing tests within asset classes, we examine extensive portfolios sorted by bond characteristics and equity characteristics. We first construct four categories of quintile portfolios based on bond CAPM beta, bond duration, bond rating, and illiquidity, totaling 20 portfolios. The monthly excess returns for these 20 portfolios range from 13 bps to 46 bps, with nearly all being significantly different from zero. After controlling for our three-factor model, the alphas of the 19 out of 20 portfolio become insignificant.[3] We further examine the model's performance in equity markets using the standard 25 size and book-to-market portfolios. Notably, our model reduces the number of portfolios with significant raw excess return from 20 to only 2. Further analysis suggests that this explanatory power is primarily driven by the credit factor, whose betas are significant across all equity portfolios, while duration and liquidity betas remain largely insignificant. This pattern indicates that our credit factor captures a pervasive market-wide risk priced in both asset classes.

We further propose a novel measure of the U.S. Treasury convenience yield derived from cross-sectional duration factors. While existing approaches like the Treasury basis of Jiang et al. (2021) rely on cross-country yield spreads, our method extracts duration factors separately from the U.S. Treasury and investment-grade corporate bond markets, then computes their return differential. This approach mitigates potential clientele effects inherent in international comparisons and directly captures the convenience yield as a domestic risk premium. Empirically, our measure exhibits strong comovement with the Treasury basis, particularly during flight-to-safety episodes, confirming its validity. The measure provides an intuitive and robust alternative for quantifying the safety premium in government bonds, with distinct advantages in isolating the pure convenience yield component from domestic market

[3] For the remaining one portfolios, which have high credit ratings, our three factors can explain half of the excess returns. Essentially, these are the firms with highest credit quality, whose returns are not fully driven by credit, duration and liquidity risks. This is consistent with the credit spread puzzle in the literature, a model incorporating crash risk may help explain the remaining one-third of the return.

dynamics.

Finally, we connect the liquidity factor to structural changes in financial regulation. By examining the volatility of the daily returns of the three factors, we observe that a significant increase in liquidity factor volatility after 2017, which coincides precisely with full implementation of post-crisis regulations under Dodd-Frank and Basel III frameworks. We establish a robust negative relationship between our liquidity factor and primary dealers' net positions in corporate bonds after 2017, supporting the transmission mechanism whereby regulatory constraints raise inventory costs, suppress market-making capacity, and consequently amplify liquidity fluctuations. Collectively, these analyses validate the relevance of our model-implied factors. Each factor – credit, liquidity, and duration – proves valuable both individually and in combination, offering researchers a comprehensive framework for analyzing financial markets.

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 contributions 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 interest rate risk or liquidity risk. Our study aims to provide a unified framework to jointly analyze these three types of risk. Moreover, the existing literature has primarily focused on the models' implication on the credit spread puzzle, including Huang and Huang (2012), Chen et al. (2008), Almeida and Philippon (2007), Bhamra et al. (2009), Chen (2010), and Huang et al. (2025). However, the implications of structural models on bond returns have been less explored, highlighting a gap that our research aims to address. By integrating liquidity and interest rate risks into the structural models, our study seeks to uncover the model-implied cross-sectional factors from corporate bond returns and further disentangle the relative importance of credit, liquidity, and duration risks over time, thereby providing new insights into this classical literature.

Our paper is also related to the growing literature on identifying a common corporate bond factor structure. This research stream begins with Fama and French (1993), who identify two key bond-market factors: the term factor and the default factor, both of which are crucial in pricing bond returns. More recently, Bai et al. (2019) propose a four-factor model, which was later retracted due to lead/lag errors identified by Dickerson et al. (2023). After correcting these statistical issues, they demonstrated that the bond Capital Asset Pricing Model (CAPM) is not dominated by either traded or non-traded factor models in the existing literature. Most existing studies adopt statistical methodologies. Kelly et al. (2023) use instrumented principal components analysis (IPCA) to propose a conditional factor model for corporate bond returns. Dickerson et al. (2023) explore the corporate bond factor zoo and find that most tradable factors are unlikely sources of priced risk, except for post-earnings announcement drift in corporate bonds. Dang et al. (2023) identify carry, duration, equity momentum, and the term structure as the most important risk factors in corporate bond markets. Dick-Nielsen et al. (2024) document replication failures in corporate bond factors and find that several equity signals can predict bond returns under their robust factor construction. In global corporate bonds, Bekaert, Santis, and Mondino (2024) identify a robust three-factor model incorporating market, maturity, and liquidity, while Deng, Hou, and Shi (2024) emphasize a two-factor framework based on market and a composite equity factor. In contrast, our study adopts a structural default model-based approach, providing a theoretical foundation for some factors identified by existing statistical methods and offering valuable economic insights into disentangling different risk factors over time.

Finally, our paper is part of the literature on studying the link between credit market and macroeconomics. The impact of macroeconomic uncertainty on financial markets has been a subject of extensive research, including the macro and financial uncertainty index developed by Jurado et al. (2015), as well as the VIX index and MOVE index. In our study, we find close link between our three factors and these uncertainty index. Moreover, a growing body of literature has shown the importance of the macroeconomic days like FOMC meetings for asset pricing (e.g., Lucca and Moench (2015), Cieslak et al. (2019), Hu et al. (2022), Pan and Peng (2024) and many others). The "pre-FOMC announcement drift" refers to the fact that the U.S. equities tend to exhibit large average excess returns higher returns on FOMC days compared to non-FOMC days. In the context of bond markets, we find similar patterns for our credit factor and duration factor, while the liquidity factor has more significant returns on Nonfarm Payroll days. Overall, our findings link each factor uniquely to specific macroeconomic events, highlighting the need for investors and policymakers to closely monitor these macroeconomic indicators to better understand financial risks.

The rest of our paper is organized as follows. Section 2 presents a structural model of default with stochastic interest rates and liquidity jump shocks. Section 3 describes the data and constructs our model-based three factors, then examines their risk premia, investigates the relative importance of credit risk, liquidity risk, and duration risk over time, and analyzes the macroeconomic drivers of these factors. Section 4 explores the empirical implications of our three-factor framework, including its ability to explain risk premia in both aggregate markets and cross-sectional portfolios, demonstrates how the duration factor can be used to construct a novel convenience yield measure, and establishes the connection between the liquidity factor and dealer' capacity. Section 5 concludes. Further details are provided in the Appendix.

2 The Model

Our model framework builds on a sequence of work by Merton (1974) and Longstaff and Schwartz (1995). We first consider a structural model of default (Merton (1974)) augmented with stochastic interest rate (Longstaff and Schwartz (1995)). Later we will introduce a jump component capturing the liquidity shock (Pan (2002), Bao et al. (2011), He and Xiong (2012)).

2.1 Default Risk and Interest Rate Risk

Under the risk-neutral measure, the aggregate output V_t follows a geometric Brownian motion

$$\frac{dV_t}{V_t} = r_t dt + \sigma_v dB_t^v \,, \tag{2}$$

where r is the short-term risk-free rate. Following Longstaff and Schwartz (1995), we assume the dynamics of r is drawn from Vasicek (1977), given by

$$dr_t = (\alpha - \beta r_t)dt + \eta dB_t^r \,, \tag{3}$$

The firm i's asset value V_t^i follows a geometric Brownian motion

$$\frac{dV_t^i}{V_t^i} = r_t dt + \beta_i \sigma_v dB_t^v + \sigma_i dB_t^i \,, \tag{4}$$

where B_t^i is an independent standard Brownian motion that generates idiosyncratic shocks specific to the firm i. β_i is the sensitivity of the firm-level systematic volatility to variation in the aggregate volatility. Therefore,

$$\frac{dV_t^i}{V_t^i} = r_t dt + \sigma dB_t \,, \tag{5}$$

where $\sigma = \sqrt{\beta_i^2 \sigma_v^2 + \sigma_i^2}$ and B_t is a standard Brownian motion.

For any security with payoff at time T contingent on the values of V and r, the price $H(V, r, T)$ follows the partial differential equation,

$$\frac{\sigma^2}{2} V^2 H_{VV} + \frac{\eta^2}{2} H_{rr} + \rho_{Vr} \sigma \eta V H_{Vr} + rVH_V + (\alpha - \beta r)H_r - rH = H_T, \tag{6}$$

For riskfree bond, following Vasicek (1977), the value of a riskless discount bond $R(r, T)$

is given by

$$R(r,T) = e^{A(T)+B(T)r}, \tag{7}$$

where

$$\begin{aligned} A(T) &= \left(\frac{\eta^2}{2\beta^2} - \frac{\alpha}{\beta}\right)T + \left(\frac{\eta^2}{\beta^3} - \frac{\alpha}{\beta^2}\right)(e^{-\beta T} - 1) - \frac{\eta^2}{4\beta^3}(e^{-2\beta T} - 1), \\ B(T) &= \frac{1}{\beta}(e^{-\beta T} - 1). \end{aligned}$$

For risky bond, following Merton (1974), the payoff for the debt holder is $\min(V_T, K)$. Therefore, the debt value can be solved by

$$P_0 = E^Q\left[e^{-\int_0^T r_t dt}\left(K - (K - V_T)I_{V_T \le K}\right)\right]. \tag{8}$$

Following Longstaff and Schwartz (1995), the bond price P_0 can be solved as follows,

Proposition 1 *The value of a risky bond under Merton with stochastic interest rate is,*

$$P_0 = KR(r,T)N(d_2) + V_0 R(r,T) e^{M(T,T)+\frac{1}{2}S^2(T)}N(-d_1), \tag{9}$$

where

$$d_2 = \frac{\ln\frac{V_0}{K} + M(T,T)}{S(T)}, \quad d_1 = \frac{\ln\frac{V_0}{K} + M(T,T) + S^2(T)}{S(T)},$$

and

$$\begin{aligned} M(t,T) &= \left(\frac{\alpha}{\beta} - \frac{\eta^2}{\beta^2} - \frac{1}{2}\sigma^2 - \frac{\rho_{vr}\sigma\eta}{\beta}\right)t + \left(\frac{\eta^2}{2\beta^3} + \frac{\rho_{vr}\sigma\eta}{\beta^2}\right)e^{-\beta T}(e^{\beta t} - 1) \\ &+ \left(\frac{r}{\beta} - \frac{\alpha}{\beta^2} + \frac{\eta^2}{\beta^3} - \frac{\eta^2}{2\beta^3}e^{-\beta T}\right)(1 - e^{-\beta T}), \end{aligned} \tag{10}$$

$$S^2(t) = \left(\frac{\rho_{vr}\sigma\eta}{\beta} + \frac{\eta^2}{\beta^2} + \sigma^2\right)t - \left(\frac{\rho_{vr}\sigma\eta}{\beta^2} + \frac{2\eta^2}{\beta^3}\right)(1 - e^{-\beta T}) + \frac{\eta^2}{2\beta^3}(1 - e^{-2\beta T}). \tag{11}$$

When r is constant, we have

$$R(r,T) = e^{-rT}, \quad M(T,T) = (r - \frac{1}{2}\sigma^2)T, \quad S(T) = \sigma\sqrt{T},$$

Hence, the bond value becomes

$$P_0 = Ke^{-rT}N(d_2) + V_0N(-d_1).$$

where $d_1 = \frac{\ln\frac{V_0}{K}+(r+\frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}$ and $d_2 = d_1 - \sigma\sqrt{T}$, which reduce to the standard result in Merton's model. For equity holder, the payoff is $\max(V_T - K, 0)$. Therefore, the equity value is

$$E_0 = V_0R(r,T)e^{M(T,T)+\frac{1}{2}S^2(T)}N(d_1) - KR(r,T)N(d_2). \tag{12}$$

For model-implied factor loadings in the bond market, we can derive the proposition following Liu et al. (2025),

Proposition 2 *The instantaneous return of bond i in excess of the riskfree rate follows*

$$\frac{dP_t^i}{P_t^i} - r_t dt = b_v^i\, dF_t^v + b_r^i\, dF_t^r, \tag{13}$$

where $dF_t^v = \sigma^v dB_t^v$, $dF_t^r = \eta dB_t^r$ and

$$\begin{aligned} b_v^i &= \frac{\partial \ln P^i(V,r)}{\partial \ln V} = \beta_i \frac{\partial \ln P^i(V^i,r)}{\partial \ln V^i} = \beta_i \frac{V^i}{P} R(r,T)e^{M(T,T)+\frac{1}{2}S^2(T)}N(-d_1), \\ b_r^i &= \frac{\partial \ln P^i(V,r)}{\partial r} = \frac{e^{-\beta T}-1}{\beta}\left[1 - \frac{\frac{f(d_2)K}{S(T)} - \frac{f(d_1)V^i e^{M(T,T)+\frac{1}{2}S^2(T)}}{S(T)} + V^i e^{M(T,T)+\frac{1}{2}S^2(T)}N(-d_1)}{KN(d_2) + V^i e^{M(T,T)+\frac{1}{2}S^2(T)}N(-d_1)}\right]. \end{aligned}$$

2.2 Adding Liquidity Shock

Following the idea in He and Xiong (2012) and Bao et al. (2011), we further introduce the liquidity shock, which arrives according to a Poisson process N_t with intensity λ. Upon the arrival of the liquidity shock, the bond investor has to sell the bond at a fractional cost of κ. To simplify the analysis, we introduce the liquidity shock in the form of a jump (Pan (2002)). The jump amplitude is $-\kappa$, which can be measured using the effective bid-ask spread from Bao et al. (2011). Therefore, for bond i at time t with jump component, we have

$$\frac{dP_t^i}{P_t^i} - r_t dt = \frac{\partial \ln P_t^i}{\partial \ln V_t}\sigma dB_t^v + \frac{\partial \ln P_t^i}{\partial r_t}\eta dB_t^r + (e^{-\kappa_i} - 1)(dN_t - \lambda dt)\,, \tag{14}$$

Hence, Proposition 2 can be further expanded to incorporate liquidity shocks,

$$\frac{dP_t^i}{P_t^i} - r_t dt = b_v^i\, dF_t^v + b_r^i\, dF_t^r + b_N^i\, dF_t^N\,, \tag{15}$$

where $b_N^i = e^{-\kappa_i} - 1$ and $dF_t^N = dN_t - \lambda dt$.

3 Estimating the Three-Factor Model

In this section, we present our model-based approach to extract three common risk factors – Credit, Liquidity and Duration – from cross-sectional corporate bond returns. As shown in (8), the bond i's price in our model $P_t^i = f(V_t, r_t, N_t)$ is a function of three state variables, where V_t is the systematic component of the firm's asset value, r_t is the stochastic interest rate, and N_t is a poisson process capturing the liquidity shocks. Associated with the three state variables of the model are the three risk factors: credit, duration, and liquidity risks. To extract these factors from cross-sectional regression, we write down the following pricing relation,

$$\frac{dP_t^i}{P_t^i} - r_t dt = b_v^i \, dF_t^v + b_r^i \, dF_t^r + b_N^i \, dF_t^N + de_t^i \,, \tag{16}$$

where $dF^v = \sigma dB_t^v$, $dF^r = \eta dB_t^r$, and $dF^N = dN_t - \lambda dt$ are the latent risk factors associated with the three state variables, whose means are zero under the risk-neutral measure Q and non-zero under the physical measure, with the factor risk premium driving the difference. Representing idiosyncratic risk, de_t^i is zero mean under both the risk-neutral and the physical measure. From proposition 2 and equation (15), for bond i, the model-implied factor loadings are $b_v^i = \partial \ln P_t^i / \partial \ln V_t$ for credit, $b_r^i = \partial \ln P_t^i / \partial r_t$ for duration, and $b_N^i = e^{-\kappa_i} - 1$ for liquidity.[4] Then we take advantage of the availability of a vast cross-section of bond returns and use the cross-sectional information to extract the time-t latent factors.

3.1 Data Description

To estimate the model and the resultant factor loading, we focus on the bond issuers with equity listed in NYSE, Nasdaq and AMEX, which are larger and more important to the economy and whose financial statements and equity market information help us measure their credit quality.

We obtain our data on bond pricing from TRACE, bond returns from WRDS, bond characteristics information from Mergent FISD, equity pricing from CRSP and issuer-level balance-sheet information from Compustat. For the purpose of studying credit pricing, we construct a sample of bonds with actively traded stocks and corporate bonds as follows.

[4] In the empirical estimation, we actually use $-\partial \ln P_t^i / \partial r_t$ as the factor loading for duration risk, which measures the sensitivity of interest rate exposure, similar to the concept of modified duration. Likewise, we use $-(e^{-\kappa_i} - 1)$ as the factor loading for liquidity risk.

We include fixed-rate dollar-denominated bonds issued by non-financial firms and exclude bonds with remaining maturity less than six months, bonds with issuance size of less than 100 thousand dollars, bonds whose issuer has less than 10 trading days in the equity market during a quarter or has missing financial statements during a quarter. To calibrate liquidity parameter at the bond-month level, we use the effective bid-ask spread derived from the gamma measure proposed by Bao et al. (2011). Therefore, we also require bonds to be actively traded, with a minimum of 11 trading days per month to facilitate the accurate calculation of the illiquidity measure. Our data sample spans a period from January 2005 to December 2023. The rationale for this time frame is that prior to 2005, public transactions were not fully disclosed on TRACE, which could potentially introduce data inconsistencies. To prevent potential data errors or outliers from driving our results, we also take the conservative treatment by winsorizing the credit spreads at lower 0.5% and upper 99.5% of the sample.

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 WRDS Bond Returns database. Following the convention, we use the Fed Constant Maturity Bonds as the reference curve and calculate the credit spread as the difference between the corporate bond yield and treasury yield of the same maturity. BondBeta is the bond beta estimated from a CAPM model in the bond market over a rolling window of past 24 months. Maturity is the bond's time to maturity in years. Rating is a numerical translation of Moody's rating: 1=Aaa and 21=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 millions of dollars. Gamma is the illiquidity measure. Callable is 1 for bonds issued with callable options.

For issuer-level equity information, we report the total market value of its equity in logarithm under EquitySize. EquityBeta is the equity beta estimated from a CAPM model in the stock market over a rolling window of past 60 months. BM is the book value of the equity to market capitalization. We further report three important inputs used to measure the credit quality of a firm. We use daily stock returns over a rolling window of past 3 months to measure equity volatility. To calculate firm leverage, we collect information on the firm's short- and long-term debt and its book value of asset from the quarterly financial statements. Leverage is calculated as the ratio of the total short- and long-term debt to the total asset value. The quarterly asset growth is computed as the growth rate of the asset value averaged over the past three years. Using these bond and equity information, we can estimate the model-based factor loadings for credit (b_{Credit}), liquidity ($b_{Liquidity}$), and duration ($b_{Duration}$).

Overall, our sample encompasses 14,761 bonds issued by 1,480 firms over the period from 2005 to 2023. The bonds in our sample exhibit a mean monthly return of 27 basis points (bps) and a credit spread of 128 bps. In terms of credit quality, the median rating stands at 8, which corresponds to Moody's Baa1 rating, indicating a relatively low credit risk profile. The median time to maturity is approximately 6 years, while the average age of the bonds is around 4 years. Regarding bond size and liquidity, the bonds in our sample are notably larger and more liquid than average. The median amount outstanding is a substantial USD 500 million, and the gamma measure, which reflects illiquidity, is 0.17, indicating a relatively high liquidity. A significant proportion of the bonds in our sample are issued with embedded call options. Shifting focus to equity market variables, the average issuer in our sample is relatively large, with a median equity size of USD 24.5 billion. This suggests that our sample is skewed towards larger corporations. The median BM is 0.4 and the median equity volatility is 0.25. The median leverage ratio is 0.37 and the median asset growth rate is 0.05. In terms of estimated factor loadings, given that the majority of the bonds in our sample are issued by high quality firms characterized by large size, low leverage, and low equity volatility, the corresponding distance-to-default measures are quite high. Under the assumption of a normal distribution, approximately 60% of the credit factor loadings in our sample are close to zero. The average liquidity factor loading is 0.77 and the average duration factor loading is 4.80.

3.2 Factor Estimation

To calibrate the model at the firm level, we need to first estimate the firm-level asset value and asset volatility. Following Moody's KMV (Kealhofer and Kurbat (2001)), we estimate the firm's asset value V and its corresponding asset volatility σ_A by solving the following non-linear equations simultaneously,

$$E_0 = V_0 R(r,T) e^{M(T,T)+\frac{1}{2}S^2(T)} N(d_1) - K R(r,T) N(d_2) \text{ and } \sigma_E = \frac{V}{E}\frac{\partial E}{\partial V}\sigma_A\,, \tag{17}$$

where E_0 is the time 0 value of the firm's equity, V_0 is the time 0 asset value of the firm, r is the risk-free rate, σ_E is equity volatility, σ_A is its asset volatility, and K is its default boundary, and T is the time horizon of interest.

To estimate monthly factors, we use the bond monthly return as the dependent variable in equation (16). For calculating the factor loadings on the right-hand side at month t, we adhere to equation (1) and utilize the most recent available information up to month t. Specifically, for balance-sheet variables, we consistently use the data from two quarters prior to month t. This includes the default boundary K, which is calculated as the sum of the firm's current debt and its long-term debt. Regarding the firm's equity value, we refer to the information from month $t-1$, calculated by multiplying the month-end stock price by the number of common equity shares outstanding. For the equity volatility σ_E, we compute it using daily equity returns spanning from month $t-3$ to month $t-1$. We require that the issuer has a minimum of 10 trading days within this three-month window to ensure sufficient data for accurate calculation. The debt maturity (T) is computed as the weighted average of preset maturities across all interest-bearing debt categories. Specifically, we assign maturities of 0.5, 1.5, 2.5, 3.5 and 7 years to debt categories dlc, dd2, dd3, dd4 and dd5, respectively, and weight each by its share of total interest-bearing debt. This consolidated measure captures the issuer's effective maturity and feeds directly into default-risk assessment.

For bond-specific variables, we use the bond's modified duration as the time horizon for discounting.[5] Additionally, we proxy the transaction cost κ with the bond's effective bid-ask spread, which is calculated from the gamma measure at month $t-1$. For interest rate parameters, we calibrate the values $\beta = 0.01$, $\alpha = 0.0005$, $\eta = 0.03$ and $\rho = -0.25$ based on interest rate data from 2005 to 2023. The risk-free rate is obtained from French's website.

With these inputs, we are able to estimate the asset value V and asset volatility σ_A using equations (17). Subsequently, we compute the factor loadings for month t by applying equation (1). This methodological framework can also be extended to estimate daily factors. We use the most recent available information from the previous month or two quarters prior to day t to calculate the factor loadings. Then, we employ bond daily returns as the dependent variable in equation (16) to extract the daily factor returns. This approach ensures consistency and accuracy in our factor estimation across different time frequencies.

Table II presents the risk premia of our three model-based factors at the monthly frequency. The results indicate that both credit and liquidity factors carry significant risk premia, particularly after the global financial crisis. Specifically, the credit factor exhibits an average premium of 24 bps (t-statistics = 1.90) from 2005 to 2023, which turned negative during the 2008 financial crisis. When focusing on the post-financial-crisis period from 2009 to 2023, the credit premium rises to 39 bps (t-statistics = 2.86). The liquidity premium averages 4 bps (t-statistics = 4.29) in the full sample and increases to 5 bps (t-statistics = 4.45) in the post-crisis sample. In contrast, we observe no significant premium for the duration factor, with an average of 1 bp (t-statistic = 0.83). However, over time, we find

[5] Our empirical estimation is conducted at the bond level to ensure sufficient cross-sectional variation for measuring the duration factor. When a firm has multiple bonds outstanding, the estimation jointly employs (i) the firm-level weighted-average maturity described above for credit-risk components and (ii) each bond's own modified duration for discount-rate components. This approach reflects the economic distinction that default risk is borne by the firm, whereas interest-rate risk is bond-specific.

interesting dynamics, particularly its strong correlation with Treasury returns. For daily factors, from 2005 to 2023, the risk premia are 0.82 bps (t-statistics = 1.32) for credit, 0.34 bps (t-statistics = 2.39) for liquidity, and 0.12 bps (t-statistics = 1.53) for duration. Focusing on the sample period from 2009 to 2023, these premia increase to 1.76 bps (t-statistics = 2.89) for credit, 0.49 bps (t-statistics = 3.20) for liquidity, and 0.16 bps (t-statistics = 1.90) for duration.

As illustrated in Figure 1, panel (a) plot the cumulative returns of the three monthly factors for credit, liquidity, and duration. Panel (b) display the cumulative returns for the daily factors. Overall, we can observe a high correlation between monthly and daily cumulative returns for each of the three factors. By running cross-sectional regression as specified in equation (16), 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. For the duration factor, it 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 in these periods. 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 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 US Treasury bonds.

3.3 The Relative Importance of Credit, Liquidity and Duration

In this subsection, we present additional empirical results to gauge and differentiate the relative importance of the credit risk, liquidity risk, and duration risk over time. Leveraging our model-based estimation framework, we can construct the three factors at a daily frequency, which allows us to promptly capture investors' concerns related to these three types of risk.

Figure 2 shows the normalized daily returns of credit factor, liquidity factor, and duration factor. Focusing first on the extreme negative outcomes of daily factors, we are able to identify episodes of flight-to-cash or dash-for-cash when our duration factor suddenly drops. Prominent examples of flight-to-cash include June 20, 2013, the day after Bernanke's taper speech; March 12, 17, and 19, 2020, events of dash for cash amid Covid-19; and June

13, 2022, when the CPI announcement for May indicates accelerating inflation. Likewise, episodes of flight-to-quality and flight-to-liquidity can be separately identified using extreme values of our credit and liquidity factors. For example, episodes of flight-to-quality captured by our credit factor include September 15, 2008 (Lehman bankruptcy), the peak of the 2008 financial crisis (early October 2008), March 9, 2020 (Covid-19), and June 13, 2022, (CPI announcement indicating accelerating inflation). Flight-to-liquidity days captured by our liquidity factor include August 8, 2011 (the black Monday due to U.S. debt ceiling crisis), October 15, 2014 (U.S. Treasury flash crash), March 23, 2020 (announcement of Fed SMCCF to provide liquidity to corporate bonds), and March 13, 2023 (SVB bankruptcy). Importantly, the clean identification of our model-based factors allows us to separately locate such important and influential episodes in history. A better understanding of their nature and origin can help us gauge the effectiveness of the policies and regulations enacted at the time.

To better assess and differentiate the relative importance of credit, liquidity, and duration risks over time, we conduct a Principal Component Analysis (PCA) on the daily returns of our three factors, credit, liquidity and duration, over a rolling window of past three months. Panel (a) of Figure 3 shows the R^2 contribution of the first three principal components (PCs) in explaining the variation in these factors. We find that the first PC accounts for approximately 60% of the total variation, while the second and third PCs account for 25% and 15%, respectively. This indicates that the first PC dominates the common movements in our factors. To further examine the contributions of each factor to the first PC, Panel (b) plots the Shapely R^2 decomposition of PC1 to overcome the overlapping information contained in three factors. Our results reveals that different factors plays key roles in explaining the first PC over time. For example, our credit factor (blue bar) can explain up to 90% of the first PC during the 2008 financial crisis and the 2016 junk bank closure, highlighting credit risk as the primary driver in these periods. Liquidity risk (red bar) emerges as the dominant factor post-2017, coinciding with regulatory changes that increased dealers' balance sheet costs. Duration risk (orange bar) takes the lead during specific events such as the 2022 interest rate hike and the 2012 European debt crisis. Overall, our analysis underscores the shifting importance of credit, liquidity, and duration risks over time.

In Figure 4, we explore the interaction effects among the three risks. Each year, we compute the correlation of daily returns across our three factors. As shown in Panel (a), the correlation between credit and liquidity risks has significantly increased since 2016. Further analysis of lead-lag relationships reveals a pronounced credit-driven liquidity effect, particularly evident after 2008. Additionally, we find a strong positive correlation between credit risk and duration risk in Panel (b), and a significant negative correlation between liquidity risk and duration risk in Panel (c). To understand the positive correlation between credit and duration factors, note that the negative duration factor typically signals lower Treasury returns (flights-to-cash), as observed post the 2022 interest rate hike, when bond investors tend to flight to quality because issuers with high credit quality are less affected by rate increases. Consequently, our credit factor turns negative, aligning with its positive correlation with the duration factor. The negative correlation between liquidity and duration factors can be driven by the fact that flights-to-duration (positive duration factor or positive treasury return) and flights-to-liquidity (negative liquidity factor) can occur simultaneously. When we combine the credit and liquidity factors to assess their total correlation with the duration factor using the weight provided in the first column of Panel B in Table IV, the negative correlation prevails, leading to an overall negative correlation with the duration factor in Panel (d) of Figure 4. This finding is consistent with the negative correlation between changes in credit spreads and Treasury yields documented by Longstaff and Schwartz (1995).

3.4 Macro Drivers of Credit, Liquidity and Duration

In this subsection, we delve into the macroeconomic 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 et al. (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 10-Year U.S. Treasury (UST) yield to measure interest rate movements, and the MOVE index to assess Treasury market uncertainty. As shown in Table III, we first conduct individual regressions of each of our three factors on these macroeconomic variables to identify their unique relationships. Subsequently, we include all macroeconomic variables in a single regression to determine which variables 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 correlated with 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 overall market volatility and economic uncertainty. The liquidity factor, on the other hand, is negatively correlated with changes in the financial uncertainty index, indicating that liquidity conditions are closely tied to the financial sector's health and the balance-sheet costs faced by intermediaries.

Additionally, the liquidity factor is positively correlated with changes in the 10-Year UST yield, which is consistent with its negative correlation with the duration factor observed in Figure 4. For the duration factor, we find it is negatively correlated with changes in the 10-Year UST yield, VIX index, and macro uncertainty index, with the 10-Year UST yield being the most significant driver. This result highlights the importance of interest rate movements in shaping duration risk, as changes in yields directly impact the value of fixed-income securities.

Moreover, leveraging the daily cross-sectional nature of our approach, we examine the performance of our three factors on specific dates, such as Federal Open Market Committee (FOMC) meetings and macroeconomic announcements. A growing body of literature has shown that U.S. equities exhibit large average excess returns in anticipation of monetary policy decisions made at scheduled FOMC meetings (e.g., Lucca and Moench (2015), Cieslak et al. (2019), Hu et al. (2022), Pan and Peng (2024) and many others). Similarly, we investigate whether the risk premia associated with our bond factors also concentrate on these important macroeconomic days. As shown in Panel B of Table II, the credit factor exhibits significant positive premia on FOMC days (11.11 bps, t-statistics = 4.05) but not on non-FOMC days (0.49 bps, t-statistics = 0.77). The economic significance of a daily 11.11 bps translates to a meaningful annual return. We observe a similar pattern for the duration factor, with returns of 1.37 bps (t-statistics = 3.02) on FOMC days versus 0.08 bps (t-statistics = 1.01) on non-FOMC days. For the liquidity factor, the average return is 0.83 bps (t-statistics = 1.22) on FOMC days and 0.33 bps (t-statistics = 2.28) on non-FOMC days.

Further examining other macroeconomic announcement days, including GDP, CPI, and Nonfarm Payroll, we find that the credit factor is particularly significant on GDP announcement days (5.92 bps, t-statistics = 2.03) but not on non-GDP days (0.57 bps, t-statistics = 0.90). The liquidity factor is highly significant on Nonfarm Payroll days (2.50 bps, t-statistics = 3.50) but not on other days (0.23 bps, t-statistics = 1.63). The duration factor is significant on GDP announcement days (0.94 bps, t-statistics = 2.65) but not on non-GDP days (0.08 bps, t-statistics = 1.02). Given the importance of these macroeconomic days for asset pricing, our findings consistently link our three factors to different types of macroeconomic events. This suggests that each factor responds uniquely to specific macroeconomic conditions, highlighting the dynamic and context-dependent nature of risk premia in financial markets.

4 The Implications of Three-Factor Model

4.1 Asset Pricing Tests

In this subsection, we first examine whether our model-based three risk factors can explain aggregate market risk premia across major asset classes, including corporate bonds, government bonds, and equities. We then extend our analysis to cross-sectional asset pricing tests within each asset class. Specifically, we construct and test portfolios sorted by various bond characteristics (such as duration, credit rating, and liquidity) and equity characteristics (including size and book-to-market ratios) to evaluate the model's performance in explaining cross-sectional return variations.

4.1.1 Explaining Aggregate Market Returns Across Asset Classes

To evaluate the performance of our three factors, we first run the following monthly regression to see if the three factors can explain the risk premia across major and important markets.

$$R_t^M - R_t^f = \alpha + \beta^{Credit} F_t^V + \beta^{Liquidity} F_t^N + \beta^{Duration} F_t^r + \epsilon_t \,, \tag{18}$$

where R_t^M is the market return for bond, stock, or treasury. F_t^V, F_t^N, and F_t^r are the three factors extracted from cross-sectional corporate bond returns in Section 3. Table IV presents the regression results. Panel A shows the mean excess returns across five market indices in US, including CorpBond (Aggregate Corporate Bond Market Index), HY (Bloomberg Barclays High-Yield Index), IG (Bloomberg Barclays Investment-Grade Index), Stock (Fama-French MktRf Portfolio), and Treasury (Bloomberg Barclays Aggregate Treasury Index), as well as three market indices for Foreign countries, including CorpBond (aggregate corporate dollar bond index by foreign issuers), SovereignEM (Bloomberg Emerging Market Sovereign Index), and SovereignEU (Bloomberg EU Sovereign Index). We observe significant risk premia in both the corporate bond and equity markets: 30 bps (t-statistics = 2.53) for US corporate bond, 49 bps (t-statistics = 2.47) for HY, 26 bps (t-statistics = 1.95) for IG, 76 bps (t-statistics = 2.55) for Stock, 34 bps (t-statistics = 2.69) for foreign corporate bond, and 36 bps (t-statistics = 2.16) for emerging market sovereign bond. For the Treasury portfolio, the average excess return is not significant after accounting for the risk-free rate, with a mean of 13 bps (t-statistics = 1.45) for US and 13 bps (t-statistics = 1.22) for EU.

Panel B reports the regression results after controlling for our three factors. Focusing on the first four market portfolios, the alphas become largely insignificant, reducing to 10 bps (t-statistics = 1.60) for US corporate bond, 16 bps (t-statistics = 1.17) for HY, 6 bps (t-statistics = 0.77) for IG, 35 bps (t-statistics = 1.62) for Stock, 7 bps (t-statistics = 0.81) for foreign corporate bond, and 8 bps (t-statistics = 0.55) for emerging market sovereign bond. To understand why our three factors can explain away the risk premia, we find that HY is more sensitive to the credit factor, while IG is more sensitive to the duration factor, followed by the liquidity factor. Consequently, all three factors have positive loadings for the aggregate US corporate bond, as well as for the aggregate foreign corporate bond and emerging market sovereign bond. For the stock market, the credit factor exhibits strong explanatory power, with a coefficient loading of 1.75 (t-statistics = 11.39). In the Treasury market, we find that the duration factor is positively correlated with Treasury returns, while the credit factor is negatively correlated, indicating a flight-to-safety from corporate bonds to Treasury bonds during market turmoil. After adjusting for these factors, the Treasury alpha becomes significantly positive (13 bps, t-statistics = 2.12). A rolling window regression over the past 24 months further reveals that the Treasury alpha is more pronounced during the post-financial-crisis period (2008–2012) and the post-COVID-19 period (2020–2022).

4.1.2 Explaining Cross-Sectional Returns Within Asset Classes

To further demonstrate the importance of our three factors, we examine their explanatory power for the risk premia of a wide range of test portfolios. We first construct four categories of quintile bond portfolios based on bond CAPM beta, bond duration, bond rating, and illiquidity, resulting in a total of 20 portfolios. As shown in Table V, the average monthly excess returns for these 20 portfolios range from 13 bps to 46 bps, with nearly all being significantly different from zero. After controlling for our three-factor bond model, the alphas of 19 out of the 20 portfolios become insignificant, particularly for those sorted by bond beta, duration, and illiquidity. For the remaining portfolio, which is the highest-rated portfolio, our three factors reduce the mean excess return from 22 bps (t-statistics = 1.88) to 11 bps (t-statistics = 2.39). Essentially, this portfolio consists of firms with the highest credit quality, whose returns are not fully driven by credit, duration, and liquidity risks.[6] Overall, our three-factor bond model is able to explain the majority of the returns in the test bond portfolios.

To evaluate the performance of our three-factor bond model on equity markets, we employ the standard 25 portfolios sorted by size and book-to-market ratio from Ken French's website. We first find that 20 out of the 25 portfolios exhibit significant raw excess returns during our sample period from 2005 to 2023. After controlling for the classic CAPM market factor in

[6] This is consistent with the credit spread puzzle in the literature, a model incorporating crash risk may help explain the remaining half of the return.

Panel A of Table VI, the number of portfolios with significant alphas drops to four. Notably, when we introduce our three-factor bond model in Panel C, this number declines to only two, indicating that our model captures a substantial portion of the risk premia in the standard stock testing portfolios, at least comparable to the CAPM model.[7]

To understand the source of this explanatory power, we delve into the factor exposures. Panels D report the betas of the stock portfolios with respect to our credit factor. The results are striking: while all credit factor betas are highly significant across the 25 portfolios, the betas for both duration and liquidity are universally insignificant. This stark contrast strongly suggests that the credit factor is the primary channel through which our model explains stock returns, as it appears to capture a pervasive, market-wide risk that is also priced in equity markets.

4.2 Duration Factor and Convenience Yield

To demonstrate the applicability of our model-implied cross-sectional factors, this subsection examines how the duration factor can serve as a measure of the convenience yield in U.S. Treasury bonds – a topic of substantial interest in the literature (e.g., Krishnamurthy and Vissing-Jorgensen (2012); Du et al. (2018); Liao (2020); Jiang et al. (2021); Jiang et al. (2023); Jiang et al. (2024)). Existing approaches, such as that of Jiang et al. (2021), infer convenience yield from the Treasury basis, defined as the yield gap between U.S. government bonds and currency-hedged foreign government bonds. However, differences in the investor bases for U.S. and foreign sovereign bonds may introduce clientele effects that also influence measured convenience yields. To better account for such effects, we propose a new estimation approach.

We first extract the duration factor from cross-sectional corporate bond returns, denoted as $Duration\_USCorp$. The same procedure is applied to the U.S. Treasury market to obtain a comparable duration factor, $Duration\_UST$. To isolate duration-related returns from credit and liquidity effects, we control for both credit and liquidity risks in the estimation and restrict the corporate bond sample to investment-grade issues. The difference between $Duration\_UST$ and $Duration\_USCorp$ then reflects the excess return of Treasuries over corporate bonds in the duration dimension, which we interpret as a measure of the U.S. Treasury convenience yield.

To assess the validity of this new measure, we compare it with the well-established Treasury basis from Jiang et al. (2021). Since our measure is expressed in returns and

[7]After controlling for the Fama-French three factors, the number of portfolios with significant alphas drops to five, similar to the results in Panel A.

the Treasury basis in yields, we plot changes in the Treasury basis against our duration-based return differential to ensure comparability. As shown in Panel A of Figure 5, the two series exhibit a strong positive comovement. For instance, in September 2008, the collapse of Lehman Brothers triggered a flight to safety, causing a sharp increase in the Treasury basis. Consistently, our duration-based measure also yield a high return that month, indicating that investors strongly preferred long-duration Treasuries over comparable investment-grade corporate bonds, even after adjusting for credit and liquidity risks. Similar co-movements are evident during other stress episodes, such as when Citigroup stood on the brink of collapse in November 2008 and during the COVID-19 outbreak in March 2020, supporting the idea that both metrics capture the convenience yield embedded in U.S. Treasuries.

We further hypothesize that the relationship between the two measures may be stronger during periods of market stress. To test this, we use the BondSafety measure from Hu et al. (2025) to identify months with pronounced flight-to-safety episodes – characterized by sharp equity declines and simultaneous Treasury rallies. As shown in Panel B, the positive association between the two convenience yield measures is indeed significantly stronger in these BondSafety months, when investor demand for safe assets is most acute. In summary, our duration-based measure of the U.S. Treasury convenience yield provides a useful and intuitive alternative to existing proxies, capturing similar economic intuition through a different methodological lens. Moreover, our measure offers distinct advantages by potentially mitigating investor clientele effects inherent in cross-country yield comparisons and providing a direct reading of the convenience yield as a risk premium in return space, thereby complementing the yield-level measure of Jiang et al. (2021).

4.3 Liquidity Factor and Dealers' Capacity

Panel (a) of Figure 6 plots the Exponentially Weighted Moving Average (EWMA) volatility of the daily returns of our three factors over a three-month rolling window, with a decay parameter of 0.98. Using volatility as a proxy for risk, we observe that credit risk (red line) is particularly pronounced during several financial upheavals: the 2008 global financial crisis, the 2011 European debt crisis, the 2016 junk bond closure, the 2020 Covid-19 pandemic, and the 2022 interest rate hike. Regarding duration risk (green line), the most notable peaks occur during the 2022 interest rate hike, the 2020 pandemic, and the 2008 financial crisis, which is consistent with our intuitions. Liquidity volatility (blue line) reaches its peak during the 2020 Covid-19 pandemic, a period marked by a dash for cash.

More importantly, liquidity volatility has grown substantially since 2017, coinciding with the full implementation of stringent regulations under the Dodd-Frank Act and Basel III.

To investigate the link between liquidity and dealer activity, Panel (b) of Figure 6 plots the EWMA volatility of our liquidity factor against primary dealers' net positions in investment-grade and high-yield corporate bonds, using data from the Federal Reserve Bank of New York (2013 – 2023).[8] The scatter plot reveals a significant negative relationship between liquidity factor volatility and dealer net positions from 2017 to 2023, while the relationship remains statistically insignificant from 2014 to 2017. This pattern is consistent with the post-crisis regulatory environment: as rising inventory costs compel primary dealers to reduce their net positions, the market's liquidity tends to become more volatile, which is precisely captured by the increase in our liquidity factor's volatility.

5 Conclusion

In this paper, we extract common risk factors – duration, credit, and liquidity – from the rich cross-section of U.S. corporate bonds. Using a structural model of default with stochastic interest-rate risk and liquidity shock, we infer these factors through bond-level loadings implied by the model. Unlike traditional approaches that rely on bond characteristics, our method leverages an arbitrage-free asset pricing model, offering a clean identification of these risks. Since 2008, the corporate bond market has faced significant shocks, such as the financial crisis, regulatory changes, COVID-19, and inflation-driven rate hikes. Our model-based factors gauge the relative importance of credit, liquidity, and duration risks amidst these uncertainties. For instance, extreme values of our factors help identify episodes of "flight-to-cash" or "dash-for-cash," as seen during the 2020 pandemic. Similarly, "flight-to-quality" and "flight-to-liquidity" events are captured by extreme values of credit and liquidity factors, respectively. This clean identification allows us to pinpoint influential historical episodes and assess policy effectiveness.

Empirically, our three-factor model shows significant risk premia for credit and liquidity, especially post financial crisis. The credit factor averaged 24 bps (t-statistics = 1.90) from 2005 to 2023, rising to 39 bps (t-statistics = 2.86) post-2009. The liquidity premium averaged 4 bps (t-statistics = 4.29) overall and 5 bps (t-statistics = 4.45) post-crisis, while the duration factor showed no significant premium, averaging 1 bp (t-statistics = 0.83). Despite this, we observed a strong correlation between the duration factor and Treasury returns over time.

We further investigate the relative importance of credit, liquidity, and duration risks over time. PCA on the three factors shows that the first principal component accounts for

[8] We omit pre-2013 data as the Fed did not separately report net positions for investment-grade and high-yield corporate bonds during that period, instead reporting only aggregate net positions that included other bond types.

approximately 60% of the total variation. Shapley R-squared decompositions reveal that the credit factor explains up to 95% of the first PC during the 2008 financial crisis and the 2016 junk bond closure, highlighting credit risk as the primary driver in these periods. Liquidity risk emerges as the dominant factor post-2017, coinciding with regulatory changes that increased dealers' balance sheet costs. Duration risk takes the lead during specific events such as the 2022 interest rate hike and the 2012 European debt crisis. Overall, our analysis underscores the shifting importance of credit, liquidity, and duration risks over time.

We also explore the macroeconomic drivers of our factors. The credit factor is negatively correlated with the VIX index and uncertainty indices, while the liquidity factor is tied to financial sector conditions. The duration factor correlates negatively with Treasury yields and uncertainty indices. Furthermore, the performance of these factors on specific dates, such as FOMC meetings and macroeconomic announcements, reveals significant premia for the credit factor on FOMC days (11.11 bps, t-statistics = 4.05) and for the duration factor (1.37 bps, t-statistics = 3.02). The liquidity factor shows significant returns on Nonfarm Payroll days. These findings link each factor uniquely to specific macroeconomic events, highlighting the dynamic nature of risk premia in financial markets.

In asset pricing tests, our model demonstrates strong explanatory power across major financial markets. The model effectively captures risk premia in both investment-grade and high-yield corporate bonds, as well as in US, foreign, and emerging market bond indices. After controlling for our factors, the significant alphas in these markets are substantially reduced. In equity markets, our model shows comparable effectiveness, with the credit factor emerging as the primary driver of stock returns. The model's robustness is further confirmed through tests on characteristic-sorted portfolios: for 20 bond portfolios sorted by CAPM beta, duration, rating, and illiquidity, our model renders 19 portfolios with insignificant alphas; similarly, for 25 size and value sorted stock portfolios, it reduces the number of portfolios with significant excess returns from 20 to just 2. These results collectively underscore our model's ability to capture fundamental sources of priced risk across diverse asset classes.

Moreover, we employ our duration factor to construct a novel measure of the U.S. Treasury convenience yield. This measure, derived from the return differential between U.S. Treasuries and investment-grade corporate bonds, offers a distinct domestic alternative to internationally-based benchmarks. It validates strongly against established measures, especially during crises, and provides a clearer channel for quantifying the safety premium embedded in government bonds by mitigating cross-country clientele effects. This application underscores the practical value of our factor-based framework in illuminating classic financial questions.

Finally, by examining the volatility of the daily returns of the three factors, we document that liquidity risk has grown substantially since 2017, coinciding with the full implementation of stringent regulations under the Dodd-Frank Act and Basel III. Consistently, we find a strong negative relationship between our liquidity factor and primary dealers' net positions in corporate bonds from 2017 to 2023. Collectively, these analyses validate the relevance of our model-implied factors. Each factor – credit, liquidity, and duration – proves valuable both individually and in combination, offering researchers a comprehensive framework for analyzing financial markets.

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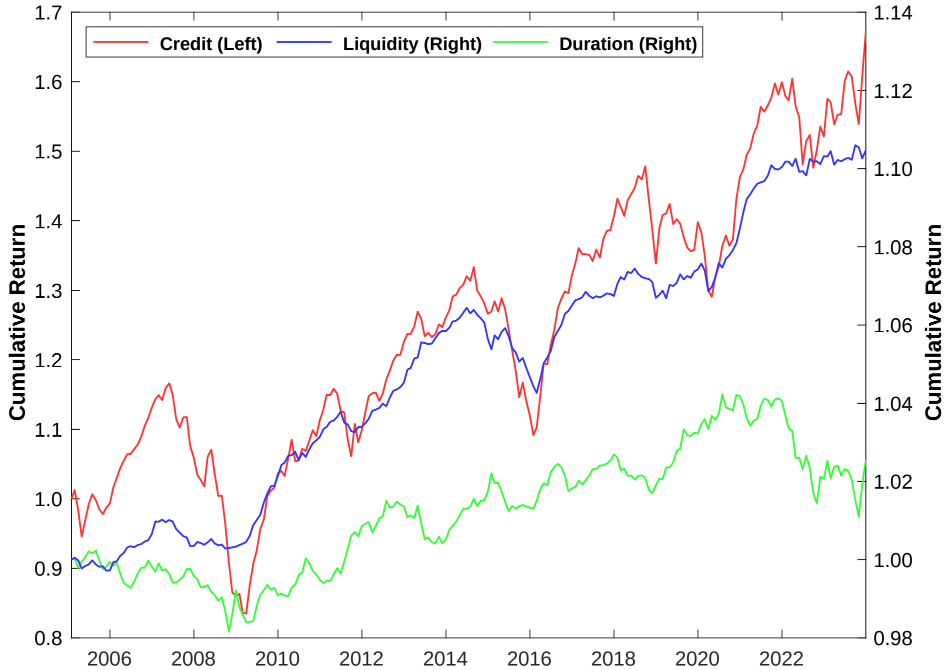
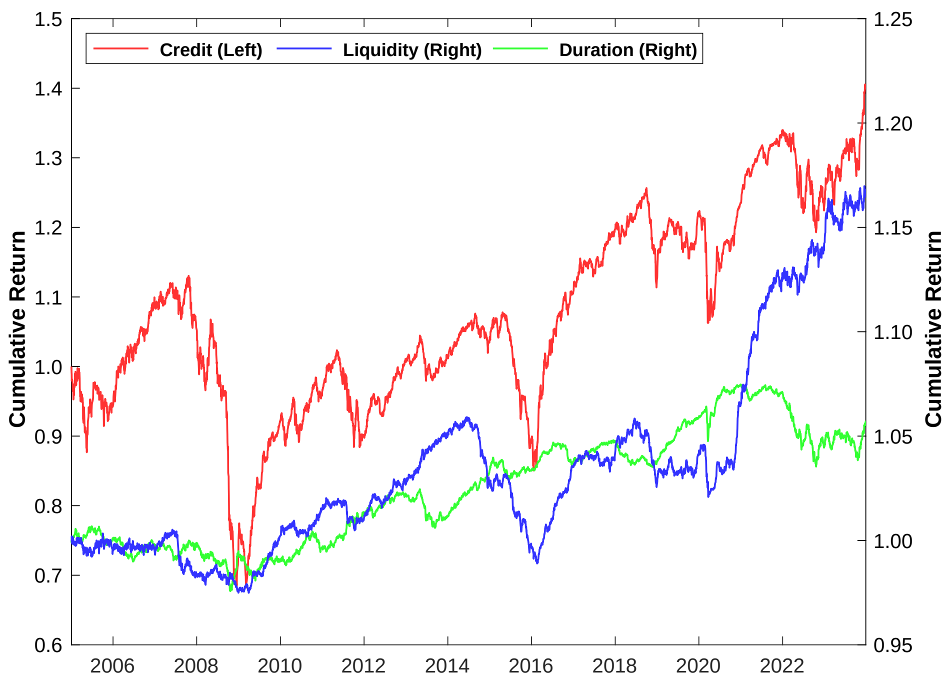


(a) Monthly Cumulative Return



(b) Daily Cumulative Return

Figure 1. This figure plots the cumulative return of our three factors – credit, liquidity, and duration – at a monthly frequency in Panel (a) and a daily frequency in Panel (b).

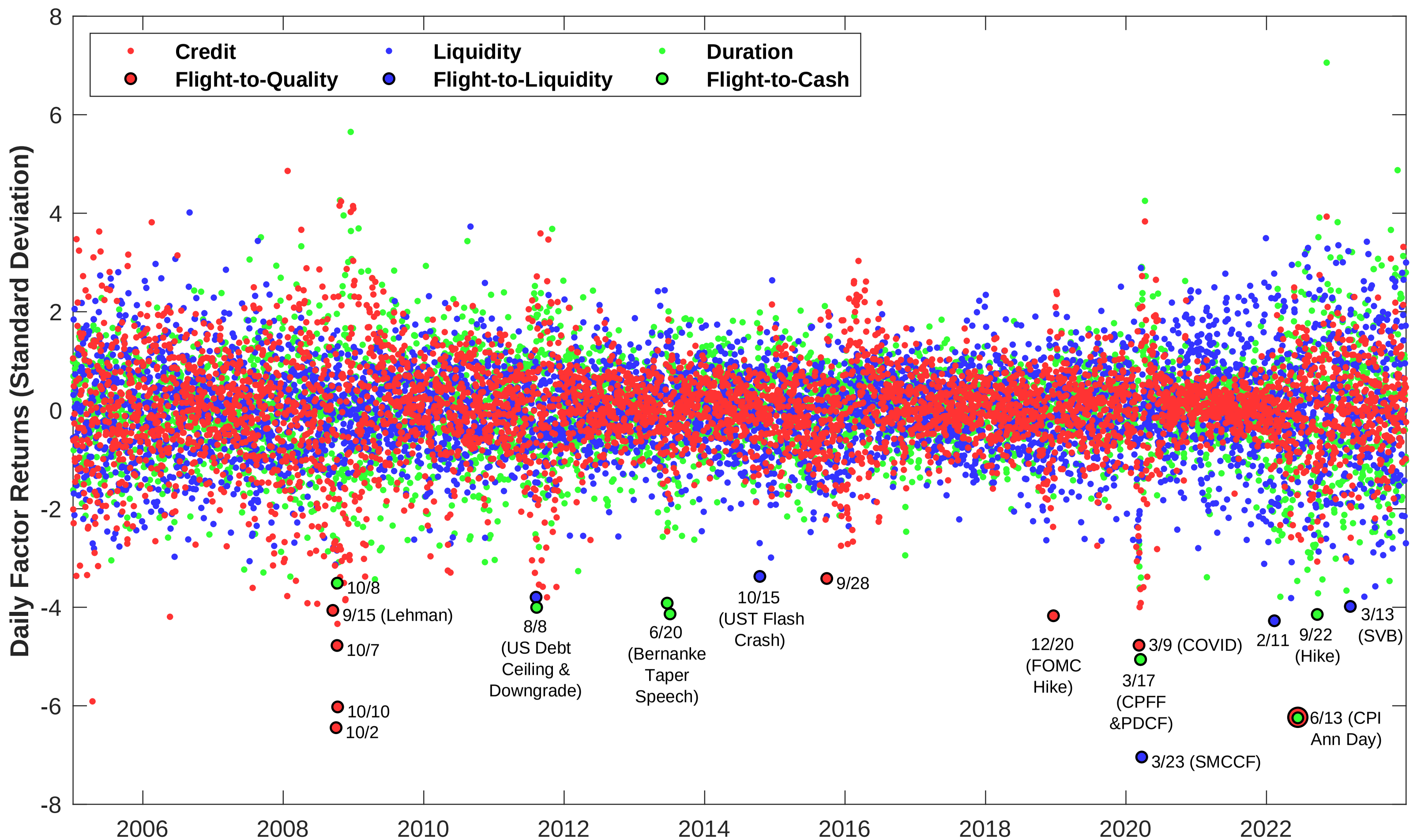
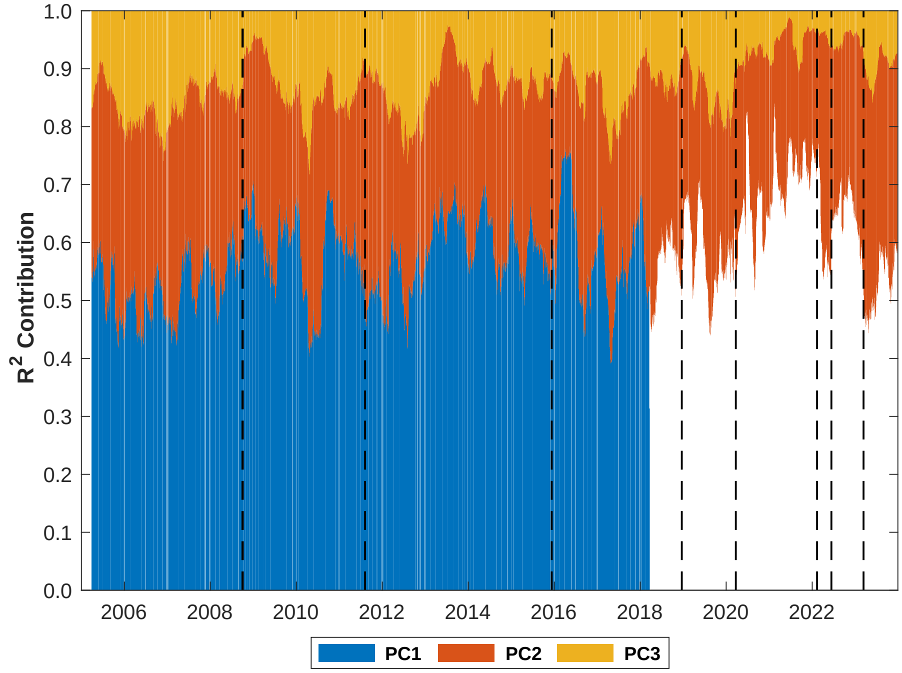
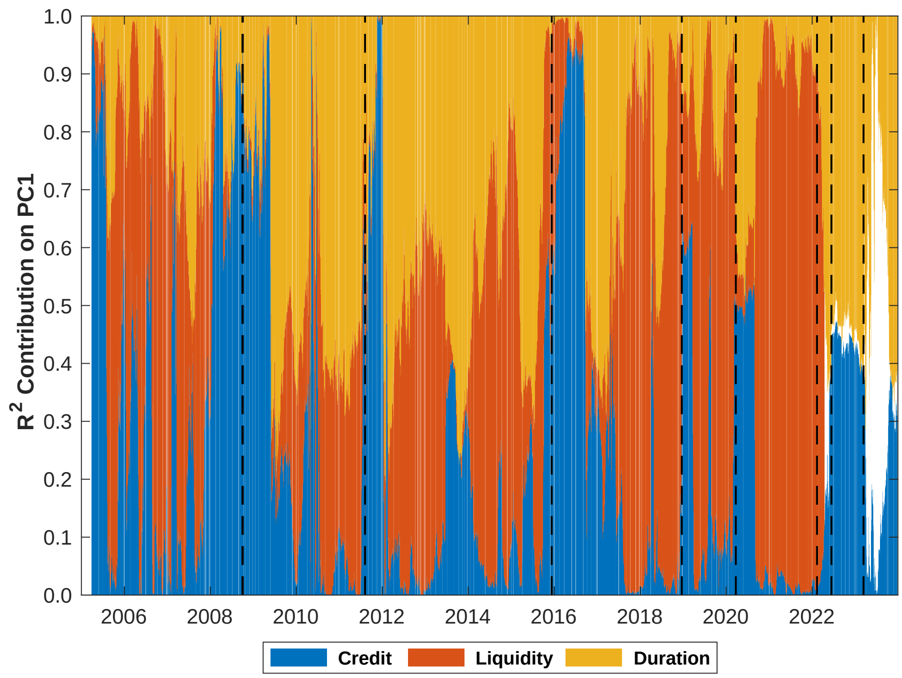


Figure 2. Factor Normalized Returns. This figure plots the normalized daily returns of our three factors: credit, liquidity and duration.

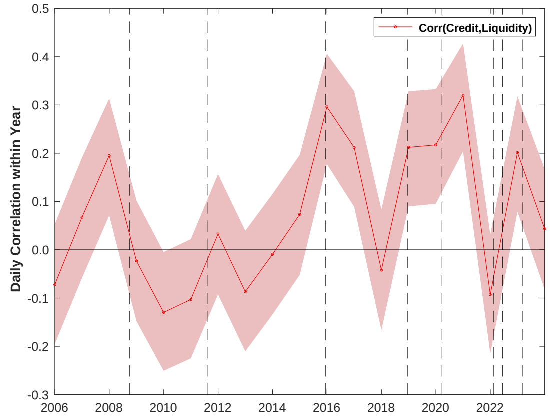


(a) R^2 Contribution for PCA

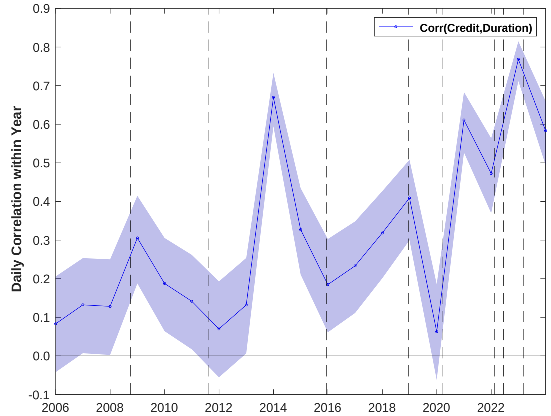


(b) R^2 Contribution for PC1

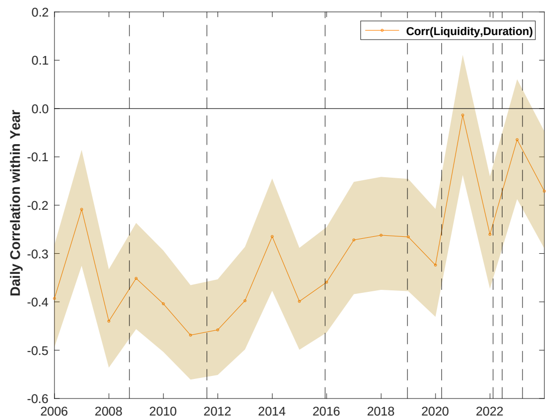
Figure 3. This figure plots the R^2 Contribution from PCA analysis based on our three factors daily returns, credit, liquidity and duration, over a rolling window of past three months. Panel (a) shows the R^2 contribution of each three PC in explaining the three factor returns. Panel (b) shows the Shapely R^2 decomposition of PC1 with respect to three factors.



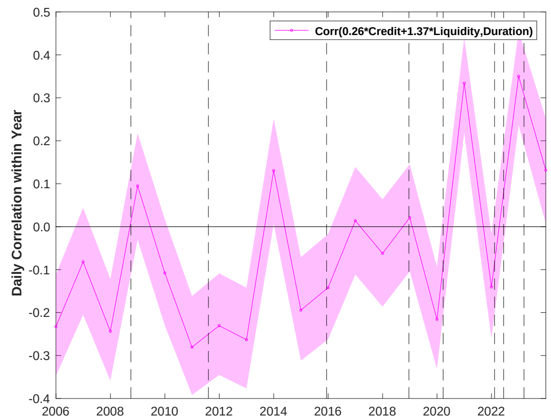
(a) Corr(Credit, Liquidity)



(b) Corr(Credit, Duration)

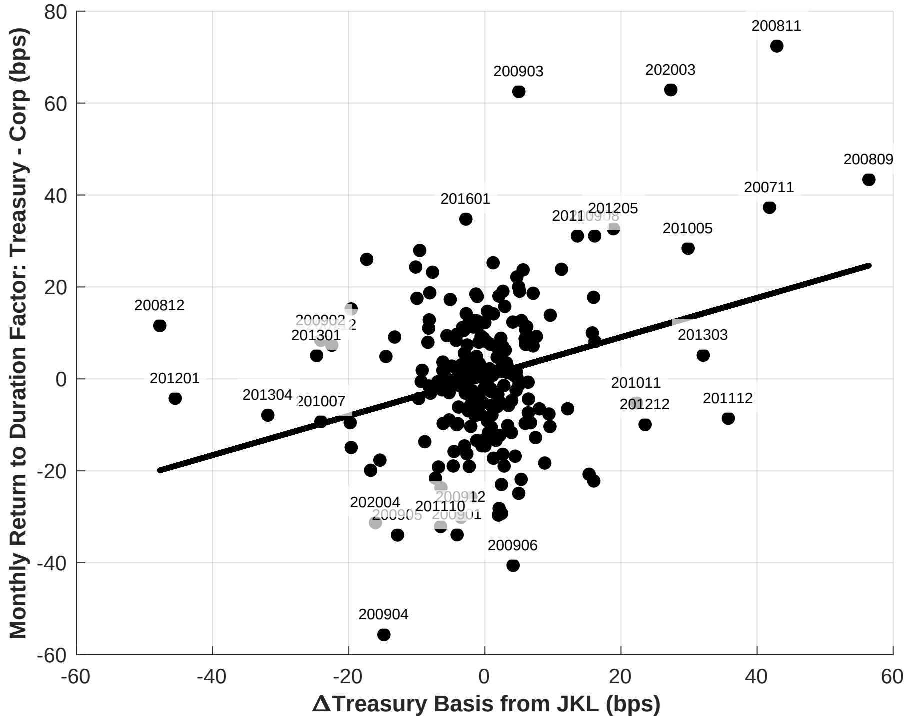


(c) Corr(Liquidity, Duration)

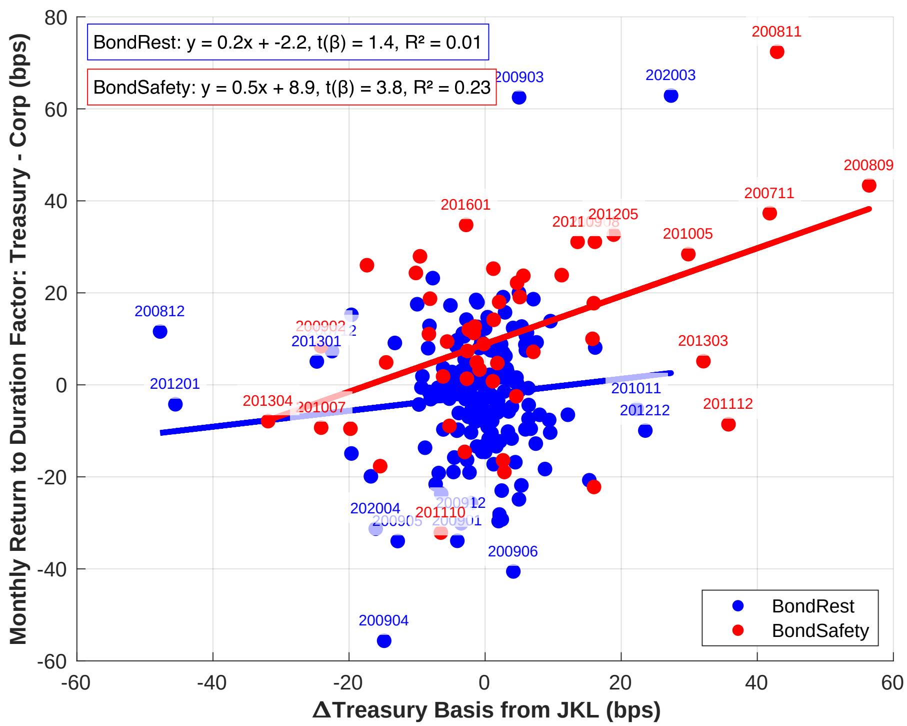


(d) Corr(Credit+Liquidity, Duration)

Figure 4. This figure shows the yearly correlation of daily returns for our three factors: credit, liquidity, and duration. Panels (a) to (c) display the pairwise correlations between these factors, while Panel (d) shows the correlation between duration and a combined measure of credit and liquidity. The weights for credit and liquidity are derived from a regression of bond market returns on the three factors. The shaded areas represent the 95% confidence intervals.

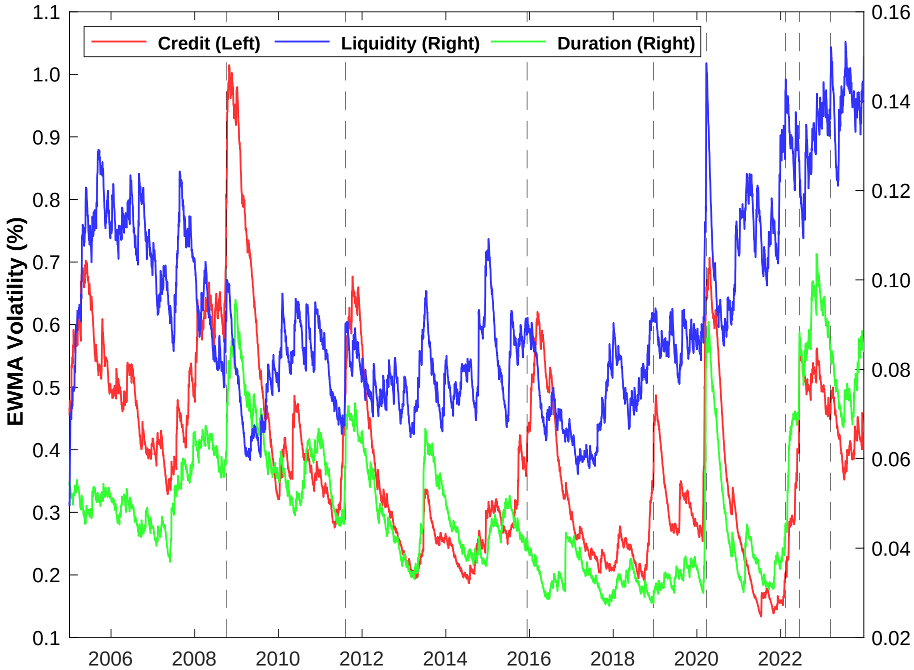


(a) Treasury Basis Comparison

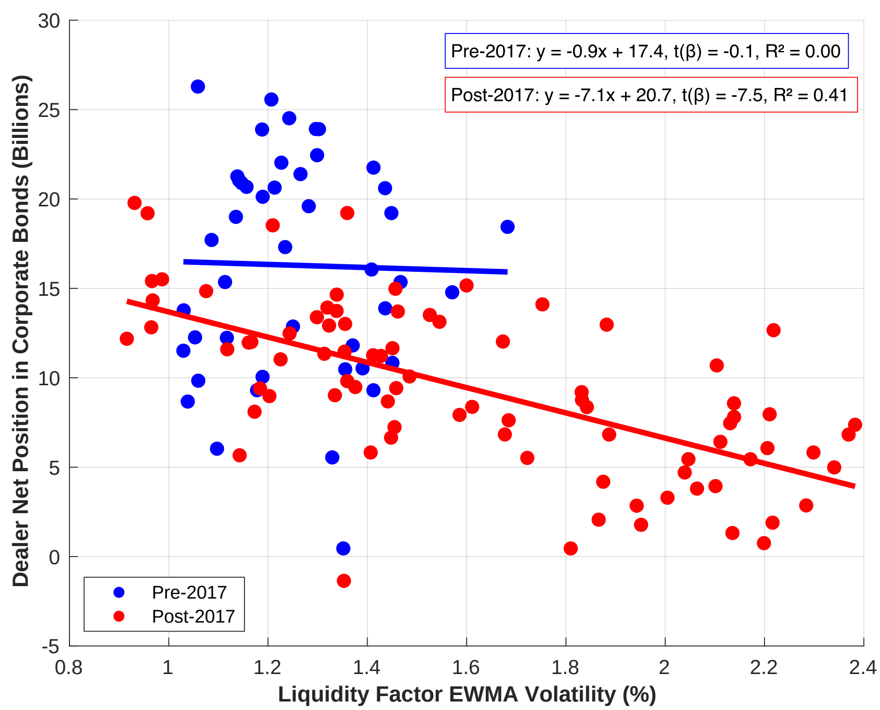


(b) Treasury Basis Comparison by Group

Figure 5. This figure plots the change in the Treasury basis from Jiang et al. (2021) against our Treasury-basis measure, defined as the monthly return difference in duration factors estimated from the U.S. Treasury and corporate-bond markets, respectively. Panel A uses the full sample; Panel B uses the subsample. BondSafety denotes months with pronounced flight-to-safety episodes – sharp equity declines coupled with 10-year Treasury rallies (See Hu et al. (2025)).



(a) Time-Series of Factor Return Volatility



(b) Liquidity Factor Volatility and Dealer Net Position

Figure 6. Panel (a) plots the EWMA volatility of our three factors, credit, liquidity and duration, with decay parameter 0.98. Panel (b) shows a scatter plot of the EWMA volatility of the liquidity factor against primary dealers' net positions in investment-grade and high-yield corporate bonds, estimated using data from the Federal Reserve Bank of New York's website.

Table I
Summary Statistics

This table reports summary statistics for our sample of bonds. The sample period is from January 2005 to December 2023. NumBonds is the number of bonds. BondRet is the month-end bond return from WRDS Bond Returns database. CreditSpread is the difference in yield between corporate bonds and Treasury bonds of the same maturity. BondBeta is the bond beta estimated from a CAPM model in the bond market over a rolling window of past 24 months. Maturity is the bond's time to maturity in years. Rating is a numerical translation of Moody's rating: 1=Aaa and 21=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 millions of dollars. Gamma is the illiquidity measure from Bao, Pan and Wang (2013). Callable is 1 for bonds issued with callable options. NumIssuers is the number of issuers. EquitySize is the log of the firm's equity size. EquityBeta is the equity beta estimated from a CAPM model in the stock market over a rolling window of past 60 months. BM is the book value of the equity to market capitalization. EquityVolatility is the annualized equity volatility. Leverage is the ratio of total short- and long-term debt to the total asset value. AssetGrowth is the average growth rate of the asset value in the past three years. b_{Credit}, $b_{Liquidity}$, and $b_{Duration}$ are the bond's factor loading associated with credit, liquidity, and duration factors, respectively.

Variable	Mean	StdDev	Min	P25	Median	P75	Max
	Bond-Level Variables						
NumBonds	14,761						
BondRet (%)	0.37	2.68	-9.25	-0.53	0.27	1.31	10.23
CreditSpread (%)	1.92	2.13	-0.09	0.75	1.28	2.22	14.11
BondBeta	1.12	0.87	-0.44	0.50	0.95	1.57	5.53
Maturity (yr)	9.47	8.53	0.50	3.26	6.13	14.05	29.99
Rating	8.59	3.33	1.00	6.00	8.00	10.00	17.00
Age (yr)	5.67	4.73	1.00	2.00	4.00	7.00	24.00
Coupon (%)	5.13	1.90	1.20	3.65	5.10	6.50	9.75
Amount	659	520	1.80	300	500	800	2850
Gamma (bps)	0.83	2.20	-1.09	0.03	0.17	0.65	16.76
Call	0.88	0.32	0.00	1.00	1.00	1.00	1.00
	Equity-Level Variables						
NumIssuers	1,480						
EquitySize (log)	23.79	1.62	18.46	22.87	23.92	24.85	27.84
EquityBeta	1.02	0.62	-0.08	0.56	0.95	1.34	3.50
BM	0.46	0.40	-0.78	0.22	0.41	0.64	2.23
EquityVolatility	0.30	0.19	0.09	0.18	0.25	0.35	1.29
Leverage	0.39	0.17	0.07	0.27	0.37	0.48	0.97
AssetGrowth	0.07	0.11	-0.17	0.01	0.05	0.10	0.53
	Estimated Factor Loadings						
b_{Credit}	0.10	0.29	0.00	0.00	0.00	0.02	2.09
$b_{Duration}$	5.87	4.30	-1.94	2.64	4.80	7.79	16.70
$b_{Liquidity}$	1.19	1.35	0.00	0.31	0.77	1.57	8.11

Table II

Factor Returns

Panel A reports the average returns and alphas for monthly factors and daily factors. Panel B reports the average daily factor returns on macro announcement days, including FOMC, CPI, Nonfarm Payroll, and GDP. Reported in square brackets are *t*-statistics. *, **, and *** indicate significant at the 10%, 5%, and 1% level, respectively.

	Panel A: Average Factor Returns and Alphas							
	Monthly (%)				Daily (bps)			
	2005-2023		2009-2023		2005-2023		2009-2023	
	Mean	Alpha	Mean	Alpha	Mean	Alpha	Mean	Alpha
Credit	0.24*	0.06	0.39***	0.13	0.82	-0.61	1.76***	-0.29
	[1.90]	[0.61]	[2.86]	[1.21]	[1.32]	[-1.07]	[2.89]	[-0.55]
Liquidity	0.04***	0.04***	0.05***	0.05***	0.34**	0.32**	0.49***	0.45***
	[4.29]	[3.98]	[4.45]	[3.98]	[2.39]	[2.23]	[3.20]	[2.88]
Duration	0.01	-0.02*	0.02	-0.02**	0.12	-0.18***	0.16*	-0.26***
	[0.83]	[-1.78]	[1.08]	[-2.20]	[1.53]	[-3.17]	[1.90]	[-4.36]
	Panel B: Daily Factor Returns on Macro Announcement Day (bps)							
	FOMC	non-FOMC	GDP	non-GDP	Nonfarm	Rest	CPI	non-CPI
Credit	11.11***	0.49	5.92**	0.57	0.92	0.81	3.82	0.67
	[4.05]	[0.77]	[2.03]	[0.90]	[0.31]	[1.28]	[1.32]	[1.05]
Liquidity	0.83	0.33**	-0.07	0.36**	2.50***	0.23	-0.22	0.37**
	[1.22]	[2.28]	[-0.11]	[2.50]	[3.50]	[1.63]	[-0.34]	[2.55]
Duration	1.37***	0.08	0.94***	0.08	-0.66	0.16**	0.26	0.11
	[3.02]	[1.01]	[2.65]	[1.02]	[-1.56]	[2.00]	[0.63]	[1.42]

Table III

Macro Drivers of Three-Factors Model (Num of STDs)

This table reports the result of time-series regressions of factor returns on a set of macro and market uncertainty variables, including the macro uncertainty index, financial uncertainty index, and real uncertainty index developed by Jurado et al. (2015), the VIX index from the CBOE, the MOVE index, and the 10-Year U.S. Treasury (UST) yield. Reported in square brackets are t-statistics. *, **, and *** indicate significant at the 10%, 5%, and 1% level, respectively.

	Panel A: Credit							
Fin Uncertainty	-0.45***							-0.18**
	[-6.53]							[-2.27]
Macro Uncertainty		-0.37***						-0.08
		[-5.72]						[-0.59]
Real Uncertainty			-0.29***					-0.02
			[-5.42]					[-0.14]
VIX				-0.51***				-0.31***
				[-7.42]				[-4.00]
MOVE					-0.33***			-0.13**
					[-4.93]			[-2.26]
Noise						-0.29***		-0.09
						[-3.95]		[-1.27]
UST10Y							0.19**	0.16**
							[2.24]	[2.04]
Constant	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00]	[-0.00]	[0.00]	[0.00]	[0.05]	[0.00]	[0.00]	[0.07]
Obs	228	228	228	228	227	228	228	227
R^2	0.20	0.13	0.08	0.25	0.10	0.08	0.03	0.35
	Panel B: Liquidity							
Financial Uncertainty	-0.37***							-0.25***
	[-6.03]							[-3.28]
Macro Uncertainty		-0.32***						-0.31*
		[-4.73]						[-1.95]
Real Uncertainty			-0.22***					0.22
			[-2.65]					[1.55]
VIX				-0.16**				0.02
				[-2.31]				[0.24]
MOVE					-0.05			-0.01
					[-0.67]			[-0.14]
Noise						-0.14**		-0.01
						[-2.31]		[-0.12]
UST10Y							0.41***	0.38***
							[5.70]	[5.76]
Constant	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.07]	[0.00]	[0.00]	[0.08]
Obs	228	228	228	228	227	228	228	227
R^2	0.13	0.10	0.04	0.02	0.00	0.01	0.17	0.28
	Panel C: Duration							
Financial Uncertainty	-0.18***							-0.05
	[-2.68]							[-0.89]
Macro Uncertainty		-0.12*						-0.03
		[-1.73]						[-0.25]
Real Uncertainty			-0.09					-0.09
			[-1.45]					[-0.93]
VIX				-0.27***				-0.24***
				[-3.70]				[-4.38]
MOVE					-0.28***			-0.04
					[-3.77]			[-0.65]
Noise						-0.15**		-0.02
						[-2.05]		[-0.33]
UST10Y							-0.73***	-0.75***
							[-12.36]	[-14.22]
Constant	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	[-0.00]	[-0.00]	[-0.00]	[-0.00]	[-0.08]	[-0.00]	[-0.00]	[-0.09]
Obs	228	228	228	228	227	228	228	227
R^2	0.03	0.01	0.00	0.07	0.07	0.02	0.53	0.64

Table IV

Explaining the Market Excess Returns

This table reports the result of monthly panel regressions of market-level excess returns on our three model-based factors: credit, liquidity and duration. We consider five market indices in US, including CorpBond (Aggregate Corporate Bond Market Index), HY (Bloomberg Barclays High-Yield Index), IG (Bloomberg Barclays Investment-Grade Index), Stock (Fama-French MktRf Portfolio), and Treasury (Bloomberg Barclays Aggregate Treasury Index), as well as three market indices for Foreign countries, including CorpBond (aggregate corporate dollar bond index by foreign issuers), SovereignEM (Bloomberg Emerging Market Sovereign Index), and SovereignEU (Bloomberg EU Sovereign Index). Panel A reports the mean excess returns. Panel B reports the regression results after controlling for our three factors. Reported in square brackets are *t*-statistics. *, **, and *** indicate significant at the 10%, 5%, and 1% level, respectively.

	Panel A: Raw Excess Monthly Return (%)							
	US					Foreign (Dollar-Denominated)		
	CorpBond	HY	IG	Stock	Treasury	CorpBond	SovereignEM	SovereignEU
Mean	0.30**	0.49**	0.26*	0.76**	0.13	0.34***	0.36**	0.13
	[2.53]	[2.47]	[1.95]	[2.55]	[1.45]	[2.69]	[2.16]	[1.22]
	Panel B: Three Factors Model							
α	0.09	0.16	0.06	0.35	0.13**	0.07	0.08	-0.02
	[1.20]	[1.17]	[0.77]	[1.62]	[2.12]	[0.81]	[0.55]	[-0.25]
Duration	6.20***	1.86	7.44***	0.88	5.49***	5.67***	5.76***	4.39***
	[10.37]	[1.52]	[14.23]	[0.64]	[16.36]	[10.68]	[6.52]	[7.33]
Credit	0.29***	1.16***	0.12*	1.75***	-0.36***	0.32***	0.47***	0.13*
	[4.48]	[7.06]	[1.95]	[11.39]	[-9.36]	[4.94]	[3.43]	[1.66]
Liquidity	1.58**	0.62	1.69**	-0.37	0.53	2.78***	2.32*	1.48*
	[2.07]	[0.39]	[2.12]	[-0.19]	[0.90]	[3.06]	[1.82]	[1.69]
R^2	0.76	0.64	0.77	0.55	0.71	0.73	0.53	0.48

Table V

Explaining the Bond Market Testing Portfolios

This table reports the result of monthly panel regressions of bond market testing portfolios on our three model-based factors: credit, liquidity and duration. We construct four categories of quintile portfolios based on bond CAPM beta (Panel A), bond duration (Panel B), bond rating (Panel C), and illiquidity (Panel D). Reported in square brackets are *t*-statistics. *, **, and *** indicate significant at the 10%, 5%, and 1% level, respectively.

	Panel A: BondBeta Sorted Portfolio					Panel B: Duration Sorted Portfolio				
	G1	G2	G3	G4	G5	G1	G2	G3	G4	G5
	Raw Excess Monthly Return					Raw Excess Monthly Return				
Mean	0.13**	0.20**	0.28**	0.33**	0.46**	0.17***	0.25**	0.30**	0.37**	0.34
	[2.01]	[2.35]	[2.26]	[2.03]	[2.11]	[2.66]	[2.37]	[2.19]	[2.25]	[1.59]
	Three Factors Model					Three Factors Model				
α	0.01	0.06	0.09	0.06	0.11	0.05	0.05	0.08	0.09	0.07
	[0.17]	[0.85]	[1.02]	[0.63]	[1.09]	[0.90]	[0.62]	[0.75]	[0.88]	[0.97]
Duration	1.95***	3.75***	5.98***	8.40***	9.77***	1.09***	2.62***	4.43***	8.45***	13.41***
	[4.43]	[7.10]	[7.65]	[10.56]	[8.47]	[2.80]	[4.65]	[5.92]	[11.30]	[17.17]
Credit	0.18***	0.13**	0.20**	0.32***	0.73***	0.24***	0.44***	0.50***	0.30***	0.19***
	[3.22]	[2.05]	[2.44]	[3.94]	[4.57]	[4.49]	[5.45]	[4.90]	[3.95]	[2.74]
Liquidity	1.20**	1.42**	1.58*	1.98*	1.47	1.04*	1.42*	1.05	2.29**	1.50*
	[1.98]	[2.05]	[1.78]	[1.86]	[1.03]	[1.88]	[1.79]	[1.07]	[2.14]	[1.86]
R^2	0.48	0.57	0.65	0.77	0.80	0.46	0.60	0.62	0.77	0.92
	Panel C: Rating Sorted Portfolio					Panel D: Illiquidity Sorted Portfolio				
	Raw Excess Monthly Return					Raw Excess Monthly Return				
Mean	0.22*	0.25*	0.27**	0.34**	0.39*	0.25*	0.23**	0.27**	0.36**	0.39**
	[1.88]	[1.95]	[1.98]	[2.19]	[1.92]	[1.81]	[2.47]	[2.24]	[2.31]	[2.06]
	Three Factors Model					Three Factors Model				
α	0.11**	0.08	0.05	0.05	0.02	0.07	0.10	0.09	0.09	-0.05
	[2.39]	[1.26]	[0.66]	[0.44]	[0.12]	[0.73]	[1.64]	[1.19]	[1.11]	[-0.47]
Duration	7.62***	7.67***	7.48***	5.26***	1.85*	5.31***	4.57***	6.07***	7.91***	8.43***
	[15.45]	[14.43]	[12.41]	[5.46]	[1.92]	[6.11]	[9.97]	[10.88]	[11.57]	[10.88]
Credit	-0.06	0.06	0.22***	0.55***	1.22***	0.42***	0.16***	0.23***	0.35***	0.58***
	[-1.32]	[1.18]	[3.13]	[4.48]	[8.40]	[3.98]	[2.62]	[3.75]	[4.85]	[6.91]
Liquidity	0.70	1.22*	1.77**	2.10	1.32	0.16	0.76	1.13	1.86**	4.63***
	[1.44]	[1.86]	[2.16]	[1.62]	[0.99]	[0.15]	[1.32]	[1.55]	[2.11]	[3.84]
R^2	0.85	0.82	0.79	0.65	0.71	0.64	0.68	0.76	0.80	0.81

Table VI

Explaining the Stock Market Testing Portfolios

This table reports the result of monthly panel regressions of Fama-French 25 Size-Value portfolios on our three model-based factors: credit, liquidity and duration. We report the regression results for CAPM Alpha (Panel A), CAPM Beta (Panel B), Bond Three Factors Alpha (Panel C), and Credit Beta (Panel D). Reported in square brackets are *t*-statistics. *, **, and *** indicate significant at the 10%, 5%, and 1% level, respectively.

	Panel A: CAPM Alpha					Panel B: CAPM Beta				
	BM1	BM2	BM3	BM4	BM5	BM1	BM2	BM3	BM4	BM5
ME1	-0.72**	-0.27	-0.34*	-0.18	-0.02	1.32***	1.20***	1.17***	1.14***	1.18***
	[-2.55]	[-1.16]	[-1.72]	[-0.82]	[-0.06]	[21.44]	[24.43]	[26.86]	[19.43]	[18.07]
ME2	-0.18	0.01	-0.02	-0.11	-0.25	1.26***	1.19***	1.18***	1.14***	1.34***
	[-0.78]	[0.04]	[-0.13]	[-0.57]	[-0.97]	[24.62]	[28.55]	[29.46]	[22.98]	[19.72]
ME3	-0.16	0.09	-0.04	-0.05	-0.16	1.20***	1.15***	1.11***	1.19***	1.27***
	[-0.90]	[0.73]	[-0.29]	[-0.29]	[-0.62]	[28.49]	[34.30]	[30.88]	[25.66]	[18.29]
ME4	0.10	0.03	-0.15	-0.07	-0.31	1.08***	1.11***	1.13***	1.13***	1.23***
	[0.79]	[0.29]	[-1.08]	[-0.41]	[-1.27]	[34.83]	[44.00]	[28.04]	[18.89]	[17.40]
ME5	0.24**	0.06	-0.00	-0.43**	-0.14	0.94***	0.87***	0.91***	1.06***	1.23***
	[2.33]	[0.77]	[-0.03]	[-2.18]	[-0.55]	[35.81]	[44.78]	[30.64]	[16.81]	[16.89]
	Panel C: Bond Three Factors Alpha					Panel D: Credit Beta				
ME1	-0.51	0.03	-0.10	0.03	0.06	2.28***	2.22***	2.13***	2.08***	2.22***
	[-1.33]	[0.08]	[-0.30]	[0.10]	[0.17]	[8.87]	[9.95]	[9.82]	[9.48]	[8.75]
ME2	0.09	0.34	0.32	0.18	0.01	2.08***	2.21***	2.18***	2.06***	2.38***
	[0.26]	[1.10]	[1.00]	[0.51]	[0.04]	[8.84]	[10.74]	[10.34]	[9.45]	[8.22]
ME3	0.14	0.45	0.27	0.20	0.04	2.01***	2.09***	2.13***	2.16***	2.17***
	[0.47]	[1.60]	[0.99]	[0.59]	[0.09]	[9.61]	[10.58]	[11.93]	[10.40]	[8.43]
ME4	0.40	0.38	0.18	0.12	-0.17	1.83***	2.02***	2.19***	1.92***	2.20***
	[1.62]	[1.45]	[0.66]	[0.35]	[-0.44]	[10.18]	[10.85]	[11.16]	[10.22]	[9.29]
ME5	0.65***	0.38*	0.27	-0.10	0.15	1.58***	1.42***	1.68***	1.94***	2.31***
	[2.90]	[1.77]	[1.15]	[-0.31]	[0.38]	[10.44]	[9.05]	[10.91]	[7.64]	[8.94]

Internet Appendix for
"Model-Based Credit, Liquidity, and Duration Factors in Cross-Sectional Corporate Bond Returns"

ZHE GENG and JUN PAN*

This Internet Appendix provides additional proofs, tables and figures supporting the main text.

I Technical Proofs

Proof of Proposition 1: From equation (8), we have,

$$\begin{aligned} P_0 &= E^Q\left[e^{-\int_0^T r_t dt}\left(K-(K-V_T)I_{V_T\le K}\right)\right]. \\ &= KR(r,T) - KE^Q\left[e^{-\int_0^T r_t dt} I_{V_T\le K}\right] + E^Q\left[e^{-\int_0^T r_t dt} V_T I_{V_T\le K}\right]. \end{aligned}$$

We first solve for the second term on the right-hand side $KE^Q\left[e^{-\int_0^T r_t dt} I_{V_T\le K}\right]$. Following Longstaff and Schwartz (1995), let $H(V,r,T)$ denote the price of a risky discount bond with maturity date T and payoff function $I_{V_T\le K}$. Let $H(V,r,T)=R(r,T)Q(V,r,T)$. Substituting into equation (6) and denoting X as the ratio V/K, we have

$$\begin{aligned} \frac{\sigma^2}{2}X^2 Q_{XX} + \frac{\eta^2}{2}Q_{rr} + \rho_{vr}\sigma\eta X Q_{Xr} + \left[r+\rho_{vr}\sigma\eta B(T)\right]XQ_X \\ + \left[\alpha-\beta r+\eta^2 B(T)\right]Q_r = Q_T, \end{aligned}$$

subject to the initial condition $Q(X,r,0)=I_{V_0\le K}$. $Q(V,r,T)$ is the probability that $\ln X_T$ is less than zero. Following the proof in the appendix of Longstaff and Schwartz (1995), $\ln X_T$ is normally distributed with mean $\ln X_0 + M(T,T)$ and standard deviation $S(T)$, where $M(t,T)$ and $S(t)$ are given by equation (10) and (11). Therefore, $KE^Q\left[e^{-\int_0^T r_t dt} I_{V_T\le K}\right] =$

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$KR(r,T)N(-d_2)$, where $d_2 = \frac{\ln \frac{V_0}{K} + M(T,T)}{S(T)}$ and $d_1 = \frac{\ln \frac{V_0}{K} + M(T,T) + S^2(T)}{S(T)}$. Similarly, we can solve for the third term $E^Q\left[e^{-\int_0^T r_t dt} V_T I_{V_T \le K}\right]$ on the right-hand side in equation (8). Hence,

$$P_0 \;=\; KR(r,T)N(d_2) + V_0 R(r,T) e^{M(T,T)+\frac{1}{2}S^2(T)} N(-d_1).$$

Proof of Proposition 2: Denote the time-t bond i price $P_t^i = f(X_t, t)$, where $X_t = (\ln V_t, r_t)$ and

$$\begin{aligned} d\ln V_t &= (r_t - \frac{1}{2}\sigma^2)dt + \sigma dB_t^v\,, \\ dr_t &= (\alpha - \beta r_t)dt + \eta dB_t^r\,, \end{aligned}$$

Applying Ito's Lemma on P_t^i, we have

$$dP_t^i = \left(\frac{\partial P_t^i}{\partial t} + \sum_{j=1}^{d} \mu_X^j \frac{\partial P_t^i}{\partial X_j} + \frac{1}{2}\sum_{j,k=1}^{d} \rho_{jk}\sigma_X^j \sigma_X^k \frac{\partial^2 P_t^i}{\partial X_j \partial X_k}\right) dt + \sum_{j=1}^{d} \frac{\partial P_t^i}{\partial X_j}\sigma_X^j dB_t^j. \qquad \text{(IA.1)}$$

where $d = 2$, $\mu_X = (r_t - \frac{1}{2}\sigma^2, \alpha - \beta r_t)'$, $\sigma_X = (\sigma, \eta)'$, $dB_t = (dB_t^v, dB_t^r)'$ and ρ is the 2×2 correlation matrix between the two brownian shocks. In our model,

$$P_t^i = E^Q\left[e^{-\int_t^T r_u du}\left(K - (K - V_T) I_{V_T \le K}\right)\right].$$

From Feynman-Kac Theorem,

$$\frac{\partial P_t^i}{\partial t} + \sum_{j=1}^{d} \mu_X^j \frac{\partial P_t^i}{\partial X_j} + \frac{1}{2}\sum_{j,k=1}^{d} \rho_{jk}\sigma_X^j \sigma_X^k \frac{\partial^2 P_t^i}{\partial X_j \partial X_k} - r_t P_t^i = 0. \qquad \text{(IA.2)}$$

Substituting to equation (IA.1),

$$dP_t^i = r_t P_t^i dt + \sum_{j=1}^{d} \frac{\partial P_t^i}{\partial X_j}\sigma_X^j dB_t^j.$$

Hence,

$$
\begin{aligned}
\frac{dP_t^i}{P_t^i} - r_t dt &= \sum_{j=1}^{d} \frac{1}{P_t^i} \frac{\partial P_t^i}{\partial X_j} \sigma_X^j dB_t^j, \\
&= \sum_{j=1}^{d} \frac{\partial \ln P_t^i}{\partial X_j} \sigma_X^j dB_t^j, \\
&= \frac{\partial \ln P_t^i}{\partial \ln V_t} \sigma dB_t^v + \frac{\partial \ln P_t^i}{\partial r_t} \eta dB_t^r.
\end{aligned}
$$