Downside Risk and the Cross-section of Corporate Bond Returns*

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Abstract

We test a model for the cross-section of corporate bond returns rooted in axiomatic preference theory. Preferences with disappointment aversion embedded in an intertemporal asset pricing framework with time-varying macroeconomic uncertainty imply a linear factor representation for expected returns. Besides the market and volatility factors, downside risk and its interactions with market and volatility risk represent three additional priced risks. Our findings strongly support the model when tested at the individual bond level, with robust evidence across alternative specifications and against the inclusion of empirically motivated factors. The model also significantly outperforms the bond CAPM for most test portfolios.

JEL Classification Codes: C31, D53, G12.

Keywords: corporate bonds, cross-sectional asset pricing, credit, downside risk, volatility risk.

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1 Introduction

Following the emergence of a factor zoo for explaining the cross-section of equity returns (e.g., Cochrane, 2011), a burgeoning literature independently proposes risk factors for the cross-section of bond returns. In influential work, Dickerson, Mueller, and Robotti (2023) document that existing empirical factor models fail to outperform a one-factor bond capital asset pricing model (CAPM). Relatedly, van Binsbergen, Nozawa, and Schwert (2024) find that existing models mostly fail to improve over the bond CAPM when returns are adjusted for the long term decline in interest rates.

We propose a test of a linear factor model for the cross-section of corporate bond returns motivated by economic theory. Specifically, we test whether an intertemporal equilibrium asset pricing model in which a representative investor has generalized disappointment aversion and the uncertainty in the economy is time-varying provides a good economic foundation for understanding the dispersion in excess corporate bond returns. Farago and Tédongap (2018) show that such a framework leads to a linear factor model with five risk factors (GDA5) that compensate investors for the return co-variation of their assets with the aggregate market and volatility risks, the downside state, and the interaction of the downside state with the market and volatility risk factors.

Corporate bonds exhibit concave payoffs, which limits their upside but exposes them to significant downside risk. Compensation for downside risk arises naturally in models with asymmetric preferences where investors' increase in marginal utility is more pronounced in downside states, such as disappointment aversion (e.g., Gul, 1991; Routledge and Zin, 2010). Moreover, there is extensive evidence that volatility risk matters for asset prices (e.g., Ang, Hodrick, Xing, and Zhang, 2006; Adrian and Rosenberg, 2008; Bloom, 2009). Thus, a model with these features emerges as a natural candidate for explaining the cross-section of corporate bond returns.

We assess the asset pricing performance of the GDA5 factor model using bond-level transactions data and find that it provides a good fit for the cross-section of excess corporate bond returns. In particular, all five factors are priced in the cross-section of corporate bond returns and their signs align with the predictions of the theory. Thus, investors command positive risk premiums for exposure to market risk, unconditionally and conditional on being in a downside state. In contrast, investors command a negative risk premium for exposure to downside states, volatility risk, and conditional downside volatility risk.

In particular, we find that investors attribute greater importance to volatility downside risk than unconditional volatility risk. Thus, our results complement and extend the findings of Chung, Wang, and Wu (2019) since we provide an economic foundation for the role of volatility risk in corporate bond returns, especially if it is high in downside states. All downside risk factors are constructed following economic theory but differ from empirical proxies of downside risk used for the analysis of bond returns (e.g., Bai, Bali, and Wen, 2019). As such, our results lend credence to the view that downside risk is priced in the cross-section of corporate bonds.

We emphasize the significance of using individual bonds rather than portfolios as test assets because of the strong factor structure in bonds. The first five (ten) principal components explain 71% (91%) of the common variation among bonds, while only 56% (70%) variation among stocks. This raises the concern that we may wrongly associate risk premiums to factors because they correlate with the common sources of variation in returns. In turn, it elevates the importance of increasing the number of test assets (Lewellen, Nagel, and Shanken, 2010). Our sample contains 37,585 bonds issued by 4,157 firms between 2002 and 2021, which is an order of magnitude larger than the maximum of 32 test portfolios used in Dickerson, Mueller, and Robotti (2023).

Moreover, grouping single assets into portfolios may lead to information loss and biased estimates of betas (see e.g. Litzenberger and Ramaswamy, 1979; Lo and MacKinlay, 1990; Berk, 2000; Conrad, Cooper, and Kaul, 2000; Phalippou, 2007). Even though grouping individual assets into portfolios has the potential for more efficient beta estimates, it also reduces their cross-sectional dispersion. Thus, Gagliardini, Ossola, and Scaillet (2016) suggest using individual securities as test assets because they maintain more observed heterogeneity in betas and make it more challenging to validate the pricing performance of risk factors.

We conduct a series of additional tests to assess the robustness of the GDA5 model. First, we examine the prices of risk of the GDA5 factors while controlling for factor betas from alternative traded and non-traded factor models proposed by the extant literature. Specifically, we consider the BBW4 model, the STK5 model, and the BND5 model (Bai, Bali, and Wen, 2019); the HKM, HKMSF and HKMNT models (He, Kelly, and Manela, 2017); the DEFTERM model (Fama and French, 1993); the stock CAPM model; the MACRO model (Bali, Subrahmanyam, and Wen, 2021b); the LIQPS and LIQAM models (Lin, Wang, and Wu, 2011); and the VOLPS and VOLAM models (Chung, Wang, and Wu, 2019).[1]

Consistent with the findings of Dickerson, Mueller, and Robotti (2023), we find that none of the factors of these alternative models have significant prices of risk with the exception of the Fama and French (1993) $TERM$ and Lin, Wang, and Wu (2011) $LIQBAM$ factors. In contrast, the GDA5 factors maintain significant prices of risk after controlling for alternative factor betas. Second, we show that our results are robust to using duration-adjusted returns (van Binsbergen, Nozawa, and Schwert, 2024), winsorized excess returns, and non-winsorized beta estimates. Third, we follow Chung, Wang, and Wu (2019) and control for an extensive list of bond characteristics. Even after controlling for all bond characteristics jointly, three of our factors, including two downside factors, still have significant prices of risk. Finally, our results are robust to alternative measures of the

[1]The DEFTERM model includes the default (DEF) and term ($TERM$) spread factors from Fama and French (1993). The MACRO model includes the $MKTB$ and the uncertainty (ΔUNC) factors from Bali, Subrahmanyam, and Wen (2021b). The LIQPS and LIQAM models include the Fama and French (1993) three factors ($MKTS$, SMB, HML), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), and the liquidity factor $LIQBPS$ or $LIQBAM$ from Lin, Wang, and Wu (2011), respectively. The VOLPS and VOLAM models include the Fama and French (1993) three factors ($MKTS$, SMB, HML), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), the volatility factor (ΔVIX) from Chung, Wang, and Wu (2019), and the liquidity factor $LIQBPS$ or $LIQBAM$ from Lin, Wang, and Wu (2011), respectively.

market and volatility factors, different values for the model parameters, and different window sizes to estimate beta.

Given the documented failure of empirical factor models to outperform the bond CAPM (e.g., Dickerson, Mueller, and Robotti, 2023; van Binsbergen, Nozawa, and Schwert, 2024) we also examine the performance of the GDA5 factor model when we use portfolios as test assets. We use eight sets of bond portfolios to assess the asset pricing performance of the GDA5 factor model, including those used by Bali, Subrahmanyam, and Wen (2021a), Dickerson, Mueller, and Robotti (2023) and Elkamhi, Jo, and Nozawa (2024). For direct comparison with the literature, we adopt the model comparison tests of Kan, Robotti, and Shanken (2013) used by Dickerson, Mueller, and Robotti (2023). While our evidence is mixed, we find that the GDA5 factors have significant prices of risk in three of the eight sets of test portfolios. More importantly, the GDA5 model has significantly higher GLS R^2 than the bond CAPM for five sets of portfolios. In these cases, the increase ranges between 0.102 and 0.351. We also confirm the results of Dickerson, Mueller, and Robotti (2023) that 13 other commonly used alternative models by and large fail to outperform the bond CAPM.

Our paper relates first and foremost to the literature on the cross-section of corporate bond returns. We provide two main contributions. First, we propose a novel set of five theory-motivated risk factors for the cross-section of corporate bonds. These risk factors are pinned down by a linear factor representation of excess returns that endogenously arises in a model where investors face aversion to downside risk and aggregate growth is heteroscedastic and unpredictable. Second, we prioritize asset pricing tests at the individual bond level and show vastly different results when we assess our model's asset pricing performance using individual securities or portfolios as test assets. Thus, we show that the pitfalls associated with dimensionality reduction by grouping assets into portfolios are especially pronounced in the case of corporate bonds.

The over-the-counter nature of bonds makes them sensitive to liquidity frictions and liquidity risk (see, e.g., Longstaff, Mithal, and Neis, 2005; Chen, Lesmond, and Wei, 2007; Dick-Nielsen, Feldhütter, and Lando, 2012; Dick-Nielsen and Rossi, 2019; Goldberg and Nozawa, 2019 among many others). Bao, Pan, and Wang (2011) and Lin, Wang, and Wu (2011) document that liquidity risk is priced in the cross-section of corporate bond returns. Other explanations for excess returns in corporate bond markets are associated with compensation for momentum risk (Jostova, Nikolova, Philipov, and Stahel, 2013) and volatility risk (Chung, Wang, and Wu, 2019; Bali, Subrahmanyam, and Wen, 2021b). Bai, Bali, and Wen (2019) propose a four-factor model that, besides a market risk premium, includes factor premiums associated with downside, liquidity and credit risk. Common to all these models is that the risk factors are empirically motivated and lack a theoretical foundation. An exception is Elkamhi, Jo, and Nozawa (2024), who propose long-run growth risk (Bansal and Yaron, 2004) as a unique factor for the cross-section of bond returns.

Dickerson, Mueller, and Robotti (2023) and van Binsbergen, Nozawa, and Schwert (2024) cast doubt on the performance of earlier factor models by showing that they largely fail to outperform a one-factor bond CAPM. Relatedly, Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) and Dickerson, Robotti, and Rossetti (2024) document the failure of existing asset pricing models for the cross-section of bond returns and their ability to replicate anomaly strategies.

Our paper also relates to the literature on preferences with disappointment aversion, which have proven successful in explaining asset pricing moments, their dynamics, and portfolio choice (e.g., Gul, 1991; Routledge and Zin, 2010; Campanale, Castro, and Clementi, 2010; Bonomo, Garcia, Meddahi, and Tédongap, 2011; Augustin and Tédongap, 2016; Dahlquist, Farago, and Tedongap, 2017; Schreindorfer, 2020; Augustin and Tédongap, 2020). Delikouras (2017) demonstrates the ability of consumption-based models with disappointment aversion to price anomalies in the cross-section of stock returns, while Farago and Tédongap (2018) successfully explain cross-sectional returns of stock, option, and currency portfolios. We complement this literature and show that the GDA5 factor model of Farago and Tédongap (2018) successfully prices the cross-section of U.S. corporate bond returns.

In Section 2, we illustrate the theoretical framework. Section 3 explains the construction of the corporate bond data set and risk factors. We examine the asset pricing performance of our model in Section 4. Section 5 concludes the paper.

2 Theoretical Framework

We introduce a framework rooted in axiomatic decision theory that rationalizes the importance of downside and volatility risk as priced factors for the cross-section of corporate bond returns. We show that these factors arise naturally in an intertemporal equilibrium asset pricing model in which the representative investor features preferences with aversion to downside risk and the economy exhibits time-varying macroeconomic uncertainty.

The capital asset pricing model (CAPM) stipulates that a security's risk premium is linearly related to the asset's return covariance with the aggregate market return (e.g., Sharpe, 1964; Lintner, 1965). Relatedly, the canonical consumption-CAPM (C-CAPM) measures a security's risk by its return covariance with aggregate per capita consumption growth (e.g., Lucas, 1978; Breeden, 1979).

Farago and Tédongap (2018) extend the C-CAPM by considering the impact on asset risk premia when investors exhibit recursive utility (Epstein and Zin, 1989; Weil, 1989) with aversion to outcomes that they experience as disappointing (e.g., Gul, 1991; Routledge and Zin, 2010).[2] In that

[2] Recall recursive lifetime utility $V_t = \left[(1-\delta)\, C_t^{1-1/\psi} + \delta \left[\mathcal{R}_t\left(V_{t+1}\right)\right]^{1-1/\psi}\right]^{1/(1-1/\psi)}$, where $0 < \delta < 1$, $\psi > 0$ and $\psi \neq 1$, define the subjective discount factor and intertemporal elasticity of substitution; the certainty equivalent is defined by $U\left(\mathcal{R}_{t+1}\right) = \mathbb{E}_t\left[U\left(V_{t+1}\right)\right]$ and $U(x) = \left(x^{1-\gamma} - 1\right)/(1-\gamma)$ if $\gamma > 0$ and $\gamma \neq 1$.

case, the stochastic discount factor (SDF) between periods t and $t+1$, $M_{t,t+1}$, is adjusted by an amount that reflects the occurrence and the intensity of disappointment:

$$M_{t,t+1}^{GDA} = M_{t,t+1}\left(\frac{1+\ell I\left(\mathcal{D}_{t+1}\right)}{1+\kappa^{1-\gamma}\ell\mathbb{E}_t I\left[\left(\mathcal{D}_{t+1}\right)\right]}\right), \tag{1}$$

where the superscript GDA denotes the SDF associated with generalized preferences for disappointment aversion, the indicator function $I(\cdot)$ is one when the condition inside the brackets is met and zero otherwise, and $\gamma \geq 0$ is the coefficient of relative risk aversion (see, e.g., Hansen, Heaton, Lee, and Roussanov, 2007; Routledge and Zin, 2010; Bonomo, Garcia, Meddahi, and Tédongap, 2011). The parameter $\ell > 0$ modulates the intensity of disappointment (Gul, 1991), while $0 < \kappa \leq 1$ generalizes the disappointment threshold to arbitrary levels below the certainty equivalent of future lifetime utility (Routledge and Zin, 2010).

The representation in Equation (1) illustrates that the case of recursive expected utility (Epstein and Zin, 1989; Weil, 1989) is nested when $\ell = 0$. Moreover, the disappointment event $\mathcal{D}_t$ is subject to lifetime utility V_t falling below a fraction κ of its certainty equivalent $\mathcal{R}(\cdot)$, that is $\mathcal{D}_t = \{V_t < \kappa\mathcal{R}_{t-1}(V_t)\}$. In this framework, the optimal portfolio choice of the representative investor implies a restriction on the conditional Euler equation where the excess return $R_{i,t}^e$ on each asset i must satisfy:

$$\mathbb{E}[M_{t,t+1}^{GDA} R_{i,t+1}^e] = 0. \tag{2}$$

Testable cross-sectional asset pricing implications of Equation (2) can be derived under two additional assumptions. First, substitute out consumption growth to express welfare valuation ratios as a function of the state variables representing the endowment economy (e.g., Epstein and Zin, 1989; Hansen, Heaton, Lee, and Roussanov, 2007; Bansal and Yaron, 2004). Second, assume that aggregate consumption growth is heteroscedastic and unpredictable (e.g., Bollerslev, Tauchen, and Zhou, 2009; Beeler and Campbell, 2012; Bonomo, Garcia, Meddahi, and Tédongap, 2011). Under these assumptions, Farago and Tédongap (2018) derive a linear five factor representation of asset excess returns given by:

$$\mathbb{E}[R_{i,t}^e] = p_W\sigma_{iW} + p_{\mathcal{D}}\sigma_{i\mathcal{D}} + p_{W\mathcal{D}}\sigma_{iW\mathcal{D}} + p_X\sigma_{iX} + p_{X\mathcal{D}}\sigma_{iX\mathcal{D}}, \tag{3}$$

with $p_{(\cdot)}$ referencing prices of risk compensating investors for asset return covariances with the log market return r_{Wt}, the market volatility $\Delta\sigma_{Wt}$, and the contingency of a downside state $I(\mathcal{D}_t)$:

$$\begin{aligned}
\sigma_{iW} &\equiv \operatorname{cov}\left[R_{it}^e, r_{Wt}\right] \\
\sigma_{i\mathcal{D}} &\equiv \operatorname{cov}\left[R_{it}^e, I(\mathcal{D}_t)\right] \\
\sigma_{iW\mathcal{D}} &\equiv \operatorname{cov}\left[R_{it}^e, r_{Wt}\cdot I(\mathcal{D}_t)\right] \\
\sigma_{iX} &\equiv \operatorname{cov}\left[R_{it}^e, \Delta\sigma_{Wt}^2\right] \\
\sigma_{iX\mathcal{D}} &\equiv \operatorname{cov}\left[R_{it}^e, \Delta\sigma_{Wt}^2\cdot I(\mathcal{D}_t)\right].
\end{aligned} \tag{4}$$

The five factor model (GDA5) in Eq. (3) shows that in the absence of disappointment aversion, only two factors command a risk premium, the market factor r_{Wt} (MKT) and the volatility factor $\Delta\sigma^2_{Wt}$ (VOL), since $p_{\mathcal{D}} = p_{W\mathcal{D}} = p_{X\mathcal{D}} = 0$. If investors experience a greater drop in utility in states that are disappointing, three additional risk premiums emerge as compensation for the asset's return covariance with the downside state factor $I(\mathcal{D}_t)$, the market downside factor $r_{Wt} \cdot I(\mathcal{D}_t)$, and the volatility downside factor $\Delta\sigma^2_{Wt} \cdot I(\mathcal{D}_t)$, which we henceforth refer to as DS, $MKTDS$, and $VOLDS$, respectively.[3]

The GDA5 model predicts that the covariance risk prices satisfy $p_W > 0$, $p_{\mathcal{D}} < 0$, $p_{W\mathcal{D}} > 0$, $p_X < 0$, and $p_{X\mathcal{D}} < 0$. Intuitively, an asset whose excess return is positively correlated with the market return commands a higher expected return to compensate investors for the exposure to the systematic risk associated with increasing marginal utility for market losses. This effect is amplified in downside states. In contrast, an asset whose excess return is positively correlated with market volatility provides a hedge against unfavorable movements in market volatility and, therefore, commands a lower risk premium. This effect is similarly amplified in downside states.

Given the preference and endowment assumptions, the downside state is explicitly described by:

$$\mathcal{D}_t = \left\{ r_{Wt} - a\frac{\sigma_W}{\sigma_X}\Delta\sigma^2_{Wt} < b \right\} \tag{5}$$

where σ_W and σ_X are the standard deviations of the market factor r_{Wt} and volatility factor $\Delta\sigma^2_{Wt}$, respectively, and where the parameters $a > 0$ and b are functions of parameters defined in the preferences and the aggregate consumption process. Equation (5) implies that downside states occur when the market return is low or when the change in market volatility is high.

To test the GDA5 model, we may further express Equation (4) as a multivariate beta pricing model:

$$\mathbb{E}[R^e_{i,t}] = p_F^\top \sigma_{iF} = \left(\Sigma_F^\top p_F\right)^\top \Sigma_F^{-1}\sigma_{iF} = \lambda_F^\top \beta_{iF}, \tag{6}$$

where the 5×1 vector $\beta_{iF} = [\beta_{iW}\ \beta_{i\mathcal{D}}\ \beta_{iW\mathcal{D}}\ \beta_{iX}\ \beta_{iX\mathcal{D}}]^\top$ may be estimated from a time-series regression of excess returns on the GDA5 factors and the 5×1 vector $\lambda_F = [\lambda_W\ \lambda_{\mathcal{D}}\ \lambda_{W\mathcal{D}}\ \lambda_X\ \lambda_{X\mathcal{D}}]^\top$ represents the corresponding prices of risk. The signs of the elements of λ_F are the same as those of p_F, i.e. $\lambda_W > 0$, $\lambda_{\mathcal{D}} < 0$, $\lambda_{W\mathcal{D}} > 0$, $\lambda_X < 0$, and $\lambda_{X\mathcal{D}} < 0$, as long as $\text{cov}(r_{Wt}, \Delta\sigma^2_{Wt}) < 0$, consistent with the leverage effect documented in the empirical literature (e.g., Black, 1976; Christie, 1982).

The GDA5 model contains a volatility factor that arises endogenously in the model because of the assumptions of stochastic consumption growth volatility and recursive utility. Thus, this framework provides a theoretical justification for the evidence that volatility risk may be negatively priced in the cross-section of corporate bond returns (Chung, Wang, and Wu, 2019), although the model emphasizes an additional compensation for volatility risk in disappointing states.

[3] A linear three factor representation emerges in a setting where aggregate consumption is homoscedastic and unpredictable or when the elasticity of substitution ψ is infinite. In that case, $p_X = p_{X\mathcal{D}} = 0$

Relatedly, the framework implies a risk premium for downside risk and for the covariances of asset returns with the market and volatility factors in downside states. Thus, the model provides a foundation for the intuition that downside risk should be priced in assets with concave payoff functions such as corporate bond returns (Bai, Bali, and Wen, 2019).

3 Corporate Bond Data and Factor Construction

We first explain the construction of the GDA5 factors (Section 3.1). We then describe the corporate bond data (Section 3.2) and present related summary statistics (Section 3.3). Appendix A provides details about the data construction with variable definitions listed in Table A.1.

3.1 Constructing the GDA5 factors

The construction of the GDA5 factors from Equation (3) requires estimates of the market return, market volatility and the downside state to compute the MKT, VOL, and DS factors. The $MKTDS$ and $VOLDS$ factors are readily available as the product of the DS factor with the MKT and VOL factors, respectively.

As a baseline approximation of the market factor (MKT), we choose the corporate bond market excess return measured as the outstanding amount-weighted average return of all bonds net of the one-month Treasury rate. This makes our results directly comparable to the existing cross-sectional bond pricing literature (Elton, Gruber, and Blake, 1995; Bai, Bali, and Wen, 2019; Dickerson, Mueller, and Robotti, 2023) and we can test for the incremental pricing power of the VOL and the three disappointment factors relative to the bond CAPM, which is difficult to outperform with empirically motivated factor models (Dickerson, Mueller, and Robotti, 2023).

Farago and Tédongap (2018) use the log return of the CRSP value-weighted portfolio as an approximation of the market portfolio to examine the cross-section of equity, option and currency portfolios. However, the aggregate corporate bond portfolio is likely a better proxy for the wealth portfolio if corporate bond market investors are primarily large institutional investors. Practically, the corporate bond market allows for a more accurate estimation of the downside factor, since downside states in the U.S. corporate bond market are more evenly distributed over the sample period, while they tend to cluster in the U.S. equity market around the 2008 Global Financial Crisis. Nonetheless, we show that our results remain intact when we approximate the market portfolio using the excess return of the CRSP value-weighted portfolio.

The computation of a bond volatility risk factor VOL is challenging due to the illiquidity of corporate bonds (e.g., Bao, Pan, and Wang, 2011; Dick-Nielsen, Feldhütter, and Lando, 2012). In the absence of a bond volatility index and high frequency bond market returns, we follow Chung, Wang, and Wu (2019) and measure bond market volatility using the Cboe VIX volatility index.[4] The VOL factor is constructed using the monthly changes in market variance calculated from the VIX index. In robustness tests, we rely on conditional variance estimates based on an EGARCH model and on the macroeconomic uncertainty index of Jurado, Ludvigson, and Ng (2015) to measure the market volatility factor.

The definition of the downside state in Equation (5) implies that the downside state factor DS depends on a and b, which are parametric functions of investor preferences and the dynamics of aggregate consumption growth. For our baseline results, we set $a = 1.00$ such that the market return and market volatility have equal weight in determining disappointing outcomes. In addition, we set $b = -0.0046$ such that the probability of disappointing outcomes p is equal to 25%. In robustness tests, we show that our main results are robust to a wide range of alternative calibration.

3.2 The corporate bond sample

Our sample consists of transactions of U.S. corporate bonds obtained from Trade Reporting and Compliance Engine (TRACE) Enhance data available at Wharton Research Data Services (WRDS). The TRACE Enhanced data provides more information compared with the TRACE Standard data and is widely used in other studies on corporate bonds (see, e.g., Dickerson, Mueller, and Robotti, 2023). We also retrieve bond information from the Mergent Fixed Income Securities Database (FISD), such as the offering date, maturity date, amount outstanding, coupon rate, coupon payment frequency, and credit rating. Our sample period is from July 2002 to December 2021.

Consistent with Dickerson, Mueller, and Robotti (2023), we apply the following filtering criteria: we remove (1) bonds issued by governments, agencies, or supranationals; (2) floating-coupon bonds and bonds with less than 1 year to maturity; (3) bonds that are not denominated in USD or whose issuer is not in the jurisdiction of the U.S.; (4) privately placed (including those through Rule-144A), asset-backed, agency-backed, equity-linked, and convertible bonds; (5) transactions that are 'when-issued', locked-in, that have special sales conditions, more than three days to settle, trade under \$5 or above \$1,000, or that have trading volume below \$10,000; (6) canceled records and we adjust corrected or reversed records following Dick-Nielsen (2009) and Dick-Nielsen (2014).

We follow Dickerson, Mueller, and Robotti (2023) and van Binsbergen, Nozawa, and Schwert (2024) to construct monthly corporate bond returns R_t as a function of end-of-month prices P_t, coupon payments C_t and accrued interest AI_t:

$$R_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}}, \tag{7}$$

[4] Cboe launched options on two corporate bond index futures only on July 10, 2023 and the synthetic corporate bond volatility index of Chen, Doshi, and Seo (2022) computed from CDX swaptions is only available since March 2012.

such that $P_t + AI_t$ represents the full (or dirty) price of the bond. The excess return is defined as the difference between the bond return and the 1-month Treasury rate, retrieved from Kenneth French's website.[5] See Appendix A for details on the implementation of the filters and the constructed of corporate bond returns.

Similar to Dickerson, Mueller, and Robotti (2023), we do not winsorize bond returns in our baseline specifications. But our main results hold when using winsorized excess returns. In addition, we construct bond duration-adjusted returns following van Binsbergen, Nozawa, and Schwert (2024) by subtracting from the bond return a duration-matched Treasury return computed off the Treasury yield curve data from Gürkaynak, Brian Sack, and Wright (2007). Our findings are also robust to the use of duration-adjusted returns.

3.3 Descriptive statistics

Our final sample consists of 1,263,743 monthly bond returns computed for 37,585 bonds issued by 4,157 firms. In Figure 1, we plot the yearly number of bonds, firms (issuers) and aggregate bond amount outstanding. The figure shows that the U.S. corporate bond market has significantly grown from \$1.45 trillion in 2002 to \$4.97 trillion in 2021. While the number of bonds has also steadily increased from 4,088 in 2002 to 6,678 in 2021, the number of issuing firms reached a peak of 869 issuing firms in 2015 and decreased thereafter to 678 by 2021.

Table 1 reports descriptive statistics of our monthly bond sample. The average excess bond return is 0.59% per month, corresponding to an annual return of 7.31%, about three quarters of the average stock excess return of issuing firms in our sample (0.81% monthly or 10.16% annually). The average monthly standard deviation of bond excess returns is 3.84%, which is an order of magnitude smaller than that of stock excess returns (8.56%).[6]

The duration-adjusted monthly return is on average 0.33% per month, close to half that of the average unadjusted bond excess return. In contrast, the average standard deviation of the duration-adjusted return is 3.82%, similar to that of the bond excess return of 3.84%. This suggests that most of the variation in bond excess returns is driven by credit component even though the level of duration-matched Treasury returns is sizeable, on average, consistent with the evidence in van Binsbergen, Nozawa, and Schwert (2024).

We use the average of Moody's and S&P's bond credit ratings, which we code using a numerical rating scale ranging from AAA=1 to D=22 for S&P's and from Aaa=1 to C=21 for Moody's. Hence, a higher value indicates a lower rating and, therefore, a higher credit risk. The average (median)

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[6] Excess stock return statistics are comparable to those reported by Hartzmark and Solomon (2022) for the CRSP value-weighted return index over a long sample from 1926-2015.

rating of the corporate bonds in our sample is 8.65 (8.04), which approximately corresponds to a Moody's rating between Baa1 and Baa2 or an S&P's rating between BBB+ and BBB. The average (median) maturity in our sample is 9.69 (6.55) years, ranging from 1 to 30 years at the 1st and 99th percentiles of the distribution. There is similarly a wide dispersion in bond size as the outstanding amount (par value) ranges from approximately \$3 million to over \$2,000 million. The average bond amount outstanding in the sample is \$542.32 million.

We compute the BPW illiquidity measure of Bao, Pan, and Wang (2011), defined as the negative value of the first-order auto-covariance of daily bond log returns within each month. We require a minimum of 2 observations within a 7 day consecutive period to recognize a daily log bond return and a minimum of 10 monthly observations for the calculation of a bond return in a month. Because of the scarcity of bond transactions, we supplement missing values with the average BPW illiquidity measure of each bond over the past 12 months. This provides us with BPW illiquidity measure for a reduced sample of 906,445 bond-month observations. Corporate bonds tend to be illiquid with positive values. The average BPW bond illiquidity is 1.02.

We complement he BPW illiquidity measure with the DFL illiquidity measure of Dick-Nielsen, Feldhütter, and Lando (2012). Using a similar approach to fill missing values with the average bond-level illiquidity measure computed over the lagged twelve months yields availability of the DFL illiquidity measure for 1,099,505 bond-month observations. The distribution of our DFL illiquidity measure resembles that reported by Dick-Nielsen, Feldhütter, and Lando (2012). Since the DFL illiquidity variable is constructed using an average of signed standardized illiquidity measures, it has both negative and positive values.

Bonds in our sample have an average (median) coupon rate of 5.65% (5.52%), ranging from less than 2% to over 10%. Bond age captures the number of years since a bond's initial offering date. It ranges from less than one year to more than 10 years, with an average of 4.60. We calculate a bond's 5% Value-at-Risk (5% VaR) following Bai, Bali, and Wen (2019), using the past 36 months of data and requiring a minimum of 24 observations. The average (median) 5% VaR is 4.55% (3.18%) ranging from less than 0.6% to over 20%. Issuing firms in our sample have on average (median) 831 (719) institutional investors. Compared to the whole CRSP-Thomson Reuters universe, firms in our sample tend to have a larger number of institutional investors (see, for example, Lewellen and Lewellen, 2022). On average, institutional investors own 66% of the equity of issuing firms, which are followed on average by 12 analysts forecasting their earnings. Analysts' forecast dispersion, i.e. the standard deviation of analysts' earnings forecasts divided by the absolute mean forecast, ranges from 0 to over 3 with an average of 0.32. Overall, our sample statistics are largely aligned with those reported by Cao, Goyal, Xiao, and Zhan (2023) and Dickerson, Mueller, and Robotti (2023). Detailed definitions of all variables are provided in Table A.1.

4 Evidence on the cross-section of U.S. corporate bond returns

We first assess the GDA5 model's ability to explain cross-sectional variation in excess returns measured at the individual bond level (Section 4.1). We then compare the GDA5 model's asset pricing performance to that of other existing factor models (Section 4.2), examine alternatives for winsorized and duration-adjusted returns (Section 4.3), examine characteristics (Section 4.4), and conduct additional robustness tests (Section 4.5). We end with a model comparison when we use corporate bond portfolios as test assets (Section 4.6).

4.1 Bond-level Fama-MacBeth regressions

One key distinction from the extant literature is that we focus our baseline analysis on explaining cross-sectional variation in excess returns measured at the individual bond level. Our choice for using bonds as test assets rather than portfolios is primarily motivated by the data structure. A principal component analysis reveals that the first five principal components (PCs) explain 71% of the variation of corporate bond returns and only 56% of the variation of stock returns.[7] The much tighter factor structure of bonds raises the importance of using a large number of test assets to assess the relevance of asset pricing models (Lewellen, Nagel, and Shanken, 2010).

Moreover, there can be vast differences in asset pricing results when using individual stocks or portfolios as test assets (Avramov and Chordia, 2006; Barras, 2019). Grouping assets into portfolios may lead to information loss and biased estimates of betas (see e.g. Litzenberger and Ramaswamy, 1979; Lo and MacKinlay, 1990; Berk, 2000; Conrad, Cooper, and Kaul, 2000; Phalippou, 2007) or a reduction in the cross-sectional dispersion of betas (Ang, Liu, and Schwarz, 2020; Lewellen, Nagel, and Shanken, 2010), making it potentially easier to find statistically significant factors when using portfolios as test assets (Gagliardini, Ossola, and Scaillet, 2016).

We test the GDA5 model using Fama and MacBeth (1973) two-pass regressions. In a first step, for each bond i, we estimate GDA5 factor betas using the following time-series regression:

$$R^e_{it} = a+\beta_{i,MKT}MKT_t+\beta_{i,DS}DS_t+\beta_{i,MKTDS}MKTDS_t+\beta_{i,VOL}VOL_t+\beta_{i,VOLDS}VOLDS_t+\varepsilon_{it}, \quad (8)$$

where R^e_{it} is the excess return of bond i in month t. We follow the literature (e.g., Dickerson, Mueller, and Robotti, 2023) and estimate Equation (8) in overlapping rolling windows of 36 months and require a minimum of 24 observations for the estimation. This yields a time-series of factor exposures (betas) for each bond in our sample. The Internet Appendix provides robustness results for alternative rolling window lengths.

[7] See Appendix Table A.2 for details on this exercise.

In a second step, we estimate the following cross-sectional regression in each month to test the GDA5 factor model:

$$R^e_{i,t+1} = \lambda_0 + \lambda_{MKT}\beta_{i,t,MKT} + \lambda_{DS}\beta_{i,t,DS} + \lambda_{MKTDS}\beta_{i,t,MKTDS} + \lambda_{VOL}\beta_{i,t,VOL} + \lambda_{VOLDS}\beta_{i,t,VOLDS} + u_{i,t+1}, \tag{9}$$

where we winsorize estimated factor betas at the 0.5% and 99.5% levels of their distribution because they are estimated over a short horizon for each monthly cross-section. However, our main results are robust if factor betas are not winsorized. We compute Newey and West (1987) standard errors with four lags based on the rule of thumb formula $L \approx T^{1/4}$ (e.g., Greene, 2018), but our results are robust to alternative number of lags.

In Table 2, we report the time-series average of pairwise cross-sectional correlation coefficients between our estimated factor betas and a battery of commonly used bond/issuer characteristics including bond coupon, maturity, rating, issuance size, age, value-at-risk, measures of illiquidity, lagged bond return, the number of institutional investors, the percentage of institutional equity ownership, number of analysts, earnings forecast dispersion, and contemporaneous stock excess return. The correlation coefficients are computed by first estimating the cross-sectional correlation of each beta with the bond characteristics and then computing the time-series average of these cross-sectional correlations. Table 2 shows that the GDA5 factor betas are generally weakly correlated with bond characteristics, suggesting that they may contain independent and incremental information on the cross-section of bond returns. The largest correlations are estimated between the MKT beta and bond maturity (0.35) and VaR5 (0.41).

We illustrate in Figure 2 the dynamics of the cross-sectional distribution for each of the five GDA5 factor betas using the cross-sectional mean, as well as the 25th, 50th and 75th percentiles of their respective distributions. These plots document a non-trivial amount of variation across all betas. For example, while the average MKT beta hovers around 1 for most of the sample, except for a dramatic spike around the 2008 Global Financial Crisis, the tails of the distribution vary more, suggesting that bonds display varying exposures to these risk factors.

We report in Table 3 the results from the two-pass Fama-MacBeth regressions of individual bond excess returns on the GDA5 factors. In column (1), we use the outstanding amount-weighted average return of all bonds in the sample minus the one-month Treasury rate as our baseline approximation for the MKT factor. All signs of the estimated coefficients (i.e., prices of risk) align with the model's prediction. Signs are positive for the market (MKT) and the market downside ($MKTDS$) factors and negative for the downside (DS), the volatility (VOL), and the volatility downside ($VOLDS$) factors. Thus, a corporate bond whose excess return is positively correlated with the market excess return, or the market excess return in downside states, commands a higher expected return to compensate investors for the exposure to systematic market risk, both unconditionally and conditionally on downside states. On the other hand, a bond whose excess return is positively correlated with downside states and the volatility factor (in or outside downside states) provides a hedge against these unfavorable conditions and, therefore, commands a lower risk premium. The coefficients of the MKT, DS, $MKTDS$, and the $VOLDS$ factors are all significant at a 5% or higher significance level. The price of risk of the VOL factor is not statistically significant. The regression intercept is statistically insignificant at conventional levels with a t-statistic of 1.14.

In columns (2), (3), and (4) of Table 3, we construct the GDA5 factors using alternative approximations for the bond market portfolio: the Bank of America Merrill Lynch Corporate Master Index (from Thomson Reuters Eikon), the Bloomberg Barclays US Corporate Bond Index, respectively, and the excess return of the CRSP value-weighted portfolio. The results across specifications are largely similar to those reported in our baseline specification reported in column (1). The main differences are that the intercept is significant at a 5% significance level and the VOL factor is significant at the 10% level in columns (2) and (4). The adjusted R^2 is around 13%-14% for all specifications with alternative candidates for the bond market factor.

Overall, we find that the GDA5 model performs well in explaining the cross-sectional variation of individual corporate bond returns and that all downside factors have significant and robust prices of risk. Our results thus suggest that, in addition to bond market risk, corporate bond investors also care about downside risk, as well as market and volatility downside risks. Moreover, bond investors appear to be more sensitive to volatility risk in downside states, as we find weaker results for the volatility risk factor, thereby complementing the results in Chung, Wang, and Wu (2019).

The success of the theoretically motivated GDA5 factor model contrasts with the findings in Dickerson, Mueller, and Robotti (2023) and van Binsbergen, Nozawa, and Schwert (2024), who show that most empirical factor models fail to outperform the bond CAPM in bond-level Fama-McBeth regressions using simple or duration adjusted excess bond returns. Relatedly, using bond portfolios as test assets, Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) and Dickerson, Robotti, and Rossetti (2024) document the failure of existing asset pricing models for the cross-section of bond returns and the disappearance of anomalies when adjusting for data errors, inconsistent methodological choices, and look-ahead bias. Our results thus emphasize the importance of theory-motivated risk factors in the ongoing effort to explain the cross-section of corporate bond returns.

In Figure 3, we report a scatter plot of the realized against the predicted mean excess returns of each bond in our sample. For the ease of visualization, we only show bonds with both realized and predicted returns between -0.50% and 1.50%. Then, we cut the x-axis (predicted excess return) into 20 bins with equal numbers of observations and estimate for each bin the average realized excess return and its bootstrapped standard error. This binned scatter plot suggests that the relation between the (aggregated) realized and predicted excess corporate bond return is approximately linear for bonds with positively predicted mean excess return. We assume that the zero-beta excess return is zero and estimate without a constant. According to the 45-degree line, the GDA5 model slightly underpredicts bond-level mean excess returns.

4.2 Comparing the GDA5 model to alternative factor models

We next compare the performance of the GDA5 factor model with that of alternative linear asset pricing models that the extant literature suggests for the cross-section of corporate bond returns.

Following Dickerson, Mueller, and Robotti (2023), we consider several traded factor models: (1) the BBW4 model of Bai, Bali, and Wen (2019) that includes the bond market factor ($MKTB$) from Elton, Gruber, and Blake (1995), the downside risk factor (DRF), liquidity risk factor (LRF), and the credit risk factor (CRF)[8]; (2) the STK5 model of Bai, Bali, and Wen (2019) that includes the Fama and French (1993) three factors ($MKTS$, SMB, HML), the Carhart (1997) momentum factor (UMD), and the Pástor and Stambaugh (2003) stock liquidity factor ($LIQS$); (3) the BND5 model of Bai, Bali, and Wen (2019) that includes the bond market factor ($MKTB$), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), the bond momentum factor ($MOMB$) from Jostova, Nikolova, Philipov, and Stahel (2013), and the bond liquidity factor ($LIQB$) from Lin, Wang, and Wu (2011); (4) the He, Kelly, and Manela (2017) two-factor model (HKM) that includes the stock market factor ($MKTS$) and the traded intermediary capital risk factor ($CPTLT$); (5) the DEFTERM model that includes the default (DEF) and term ($TERM$) spread factors from Fama and French (1993); (6) the stock CAPM model that includes only the $MKTS$ stock market factor; (7) the HKMSF model that includes the single $CPTLT$ factor examined by Dickerson, Mueller, and Robotti (2023). Table A.1 provides details about data sources and factor constructions.

Table 4 reports the pairwise correlation coefficients between the traded and the GDA5 factors. We highlight those coefficients that are statistically significant at the 1% level in bold with an asterisk. MKT and DS are negatively correlated by construction. MKT and VOL are negatively correlated, consistent with a leverage effect (e.g., Black, 1976; Christie, 1982). As in Dickerson, Mueller, and Robotti (2023), the correlation coefficients between DRF (LRF) and MKT (i.e. $MKTB$, the bond market factor) is high, i.e. 83% (72%). The correlation between DRF and LRF is also as high as 81%. In addition, the 48% correlation between $MKTS$ and MKT indicates only limited co-movement between the stock and bond market. Downside risk factors are mostly weakly correlated with other factors, again suggesting that they main contain information about the cross-section of corporate bond returns beyond those factors commonly used in the literature.

We repeat our baseline estimations and control for the betas of the alternative factor models in the second step of the Fama-MacBeth regressions. Specifically, we follow Dickerson, Mueller, and Robotti (2023) and van Binsbergen, Nozawa, and Schwert (2024) and estimate all factor betas for each model jointly. Since the bond market factor ($MKTB$) is common to the GDA5, BBW4, and BND5 models, we only include GDA5's market factor for these specifications that include the

[8]To avoid confusion with the notation, we use "MKT" to denote the market factor of the GDA5 model. Hence, we use "$MKTS$" to denote the stock market factor and "$MKTB$" to denote the bond market factor. In our main specification, we use $MKTB$ as MKT in the GDA5 model.

BBW4 and BND5 models. We nonetheless show in the appendix that including their market factors does not affect our results.

Table 5 reports our results. In column (1), we report the baseline regression from column (1) Table 3 for comparability. In column (2) we include all of the GDA5 factor betas and the BBW4's DRF, LRF, and CRF factor betas in the second-stage cross-sectional regression. The sample size decreases slightly because the DRF factor is constructed using the bond's 5% value-at-risk, which requires a 36-month estimation period. All GDA5 factors have significant prices of risk at the 1% significance level and have similar coefficients to those reported in column (1). In contrast, none of the DRF, LRF, and CRF factors have significant prices of risk at conventional significance levels largely confirming the findings of Dickerson, Mueller, and Robotti (2023).

When we add the STK5 factors in column (3) of Table 5, all downside factors remain significant at a 5% or higher significance level, while the MKT factor is significant at the 10% level. None of the STK5 factors have significant risk prices. Similarly, we maintain strongly significant risk premiums associated with the GDA5 factors when we include the BND5 factors (excluding $MKTB$) in column (4). We face again a sample reduction because the $LIQB$ factor in the BND5 model depends on the liquidity beta that is estimated using 60-months rolling windows as in Lin, Wang, and Wu (2011) and Bai, Bali, and Wen (2019). None of BND5 factors have significant prices of risk.

In columns (5), (6), (7), and (8) we follow Dickerson, Mueller, and Robotti (2023) and successively include the $MKTS$ and $CPTLT$ factor betas, the DEF and $TERM$ factor betas, and the $MKTS$ and the $CPTLT$ factors on a standalone basis. While neither of the alternative traded factors are statistically significant, we find that in particular the downside risk and downside volatility risk factors remain highly statistically significant. $MKTDS$ only loses significance in the specification in column (6), while we find weaker results for the unconditional market and volatility factors.

In Table 6, we further consider the performance of the GDA5 factors when we control for alternative non-traded factors proposed in the literature: (1) the MACRO model that includes the $MKTB$ and the uncertainty (ΔUNC) factors from Bali, Subrahmanyam, and Wen (2021b); (2) the LIQPS model that includes the Fama and French (1993) three factors ($MKTS$, SMB, HML), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), and the Pastor-Stambaugh bond liquidity factor $LIQBPS$ from Lin, Wang, and Wu (2011); (3) the LIQAM model that includes the Fama and French (1993) three factors ($MKTS$, SMB, HML), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), and the Amihud bond liquidity factor $LIQBAM$ from Lin, Wang, and Wu (2011); (4) the VOLPS model that includes the Fama and French (1993) three factors ($MKTS$, SMB, HML), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), the Pastor-Stambaugh bond liquidity factor $LIQBPS$ from Lin, Wang, and Wu (2011), and the volatility factor (ΔVIX) from Chung, Wang, and Wu (2019); (5) the VOLAM model that includes the Fama and French (1993) three factors ($MKTS$, SMB, HML), the default (DEF) and term ($TERM$) spread factors from Fama and French (1993), the

Amihud bond liquidity factor $LIQBAM$ from Lin, Wang, and Wu (2011), and the volatility factor (ΔVIX) from Chung, Wang, and Wu (2019); (6) the HKMNT model that includes the stock market factor ($MKTS$) and the non-traded intermediary capital risk factor ($CPTL$) from He, Kelly, and Manela (2017). See Table A.1 for details on the data and factor construction.

The results of these model performance comparisons against non-traded factors largely paint a similar picture than that observed for traded factors. Compared to the baseline results in column (1) of Table 6, the majority of the GDA5 factors maintain significant prices of risk with similar coefficient magnitudes. In particular, our three downside risk factors are significant across all specifications, except for DS, which loses significance in the VOLAM model specification reported in column (6).

Moreover, we find that almost all non-traded factors are estimated with insignificant prices of risk when they are estimated jointly with the GDA5 model, except for the $TERM$ and $LIQBAM$ factors. This result resonates with Dickerson, Mueller, and Robotti (2023), who also find that the $TERM$ factor has a significant price of risk with t-statistic below 2. However, they find that $LIQBAM$ is insignificant in the LIQAM model. Table 4, which reports the pairwise correlation coefficients between the GDA5 and non-traded factors indeed suggests that our GDA5 factors may contain independent explanatory power for the cross-section of bond returns because their correlations are mostly weak.

4.3 Duration-adjusted and winsorized excess returns

van Binsbergen, Nozawa, and Schwert (2024) document that the decline in discount rates over the past decades has led to ex-post positive return realizations for long-duration assets such as corporate bonds. To account for this impact in their asset pricing tests, the authors construct duration-adjusted returns by subtracting a duration-matched Treasury bond return. We follow their approach and use duration-adjusted bond returns as the dependent variable in our Fama-MacBeth regressions for robustness.

Column (1) of Table 7 suggests that our main results hold when we use duration-adjusted returns. Four out of five GDA5 factors are significant at a 5% level with similar coefficients to those in our baseline specification, while the unconditional volatility factor VOL is statistically insignificant. Both the magnitude and the t-statistic of the intercept are smaller compared to the benchmark regression, suggesting that primarily the intercept estimate may be driven by the long-term decline in discount rates.

In our benchmark specification, we do not winsorize because Dickerson, Mueller, and Robotti (2023) argue that it could bias the estimations while Dickerson, Robotti, and Rossetti (2024) suggest that it may introduce a look-ahead bias. A similar argument is made for options by Duarte, Jones, Khorram, Mo, and Wang (2024). In contrast, using bond portfolios as test assets, Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023) suggest that winsorizing returns may alleviate data errors in bond prices, even if they may incorrectly remove correct outliers. To alleviate the concern that the performance of the GDA5 model is driven by outliers in bond returns, we, therefore, repeat our baseline Fama-MacBeth regressions using excess returns that are winsorized at the 1% and 99% level over the whole sample.

The findings in column (2) of Table 7 suggest that our results are strikingly similar with or without winsorizing returns, if not stronger. All of the GDA5 factors are significant at a 5% or higher significance level, including the VOL factor, which was not significantly priced in our main specification.

Finally, to alleviate the concern that our results may be driven by the cross-sectional winsorization of factor betas, we report in column (3) of Table 7 Fama-MacBeth regressions without any cross-sectional winsorization of factor betas. This test further suggests that our benchmark results are robust since the coefficient estimates and the explanatory power are similar to those in our main results reported in column (1) of Table 3.

4.4 Controlling for bond characteristics

Daniel and Titman (1997, 2012) suggest that stock characteristics explain the cross-sectional variation in stock returns rather than betas. Indeed, the literature documents that bond characteristics have significant explanatory power in the cross-section of corporate bond returns (Bai, Bali, and Wen, 2019; Lin, Wang, and Wu, 2011; Chung, Wang, and Wu, 2019). We, therefore, examine whether the risk prices of the GDA5 factors are subsumed by bond/issuer characteristics, including bond size, maturity, rating, coupon, 5% VaR (VaR5), age, BPW illiquidity (Bao, Pan, and Wang, 2011), DFL illiquidity (Dick-Nielsen, Feldhütter, and Lando, 2012), lagged bond return, number of institutional investors, share of institutional ownership, number of analysts, dispersion in the earnings forecast, and contemporaneous stock excess return. See Table A.1 for detailed variable definitions.

Table 8 reports our results. For ease of comparison, in column (1), we repeat our main specification from Table 3. In columns (2)-(15), we then successively add individual bond characteristics one by one as control variables in the second-stage cross-sectional regressions. The results suggest that the magnitude and significance of the risk prices of the GDA5 factors remain largely similar across most specifications. One exception is the downside risk factor DS, which loses significance in specifications with a non-trivial drop in sample size due to less populated data for information on institutional investor, analysts' forecast dispersion, and contemporaneous stock excess return. Note that most bond characteristics do not have significant incremental explanatory power for the cross-section of corporate bond returns beyond GDA5 factor betas, except for the lagged bond return and contemporaneous stock excess return, and to a certain degree the share of institutional ownership and the forecast dispersion.

In column (16) of Table 8, we add all of the bond characteristics simultaneously. This specification shows that $MKTDS$, VOL, and $VOLDS$ remain statistically significant at a 5% or 10% level.

4.5 Robustness

We conduct a series of robustness tests to ensure the validity of our results. We briefly discuss the nature of the additional exercises and provide details in Appendix Sections B and C.

In Table A.3, we construct alternative measures of the volatility factor. In column (1), we report results from our main specification. In column (2), we report results with conditional volatility estimated using an EGARCH model (Nelson, 1991). In column (3), we use the Jurado, Ludvigson, and Ng (2015) macroeconomic uncertainty index to approximate market volatility since Bali, Subrahmanyam, and Wen (2021b) document its importance for the cross-section of corporate bond returns. Our findings in Table A.3 suggest that the choice of volatility is immaterial for our results.

The estimation of the downside state factor in Equation (5) depends on values for parameters a and b. The latter is implicitly defined through the probability of occurrence of disappointing states. In our baseline specification, we choose $p = 25\%$. The results in Table A.4 suggest that different values of $p \in \{10\%,15\%,20\%\}$ do not impact our conclusions that the GDA5 model explains the cross-section of corporate bond returns. Relatedly, our benchmark specification is based on $a = 1.00$, which gives equal weight to the market and volatility factors in determining downside states. Similarly, as we show in Table A.5, different values of parameter $a \in \{0.50,0.75,1.25\}$ yield similar conclusions.

Next, we consider alternative window lengths to estimate the factor betas, including rolling windows with 48, 60, and 72 months of lagged data, respectively. Table A.6 reports that across all different specifications, the statistical significance and magnitude of the estimated coefficients are similar to our benchmark results which are based on 36 months of lagged data. In Table A.7, we vary the lags for the Newey-West standard error correction between 2, 3, 5, and 6, and find that our results do not depend on the choice of lags. Finally, in Table A.8, we conduct additional tests to show that the pricing power of the GDA5 model is robust to including the BBW4 or BND5 market factor betas, respectively.

4.6 Portfolios as test assets

The much tighter factor structure of corporate bond returns compared to stock returns attaches a greater importance to testing the GDA5 factor model at the individual bond level (Lewellen, Nagel, and Shanken, 2010). For completeness and comparison with the literature, we also examine whether the GDA5 factor model explains the cross-section of bond returns when we use portfolios as test assets, even though grouping assets into portfolios may lead to information loss and can reduce the cross-sectional dispersion of betas (e.g., Ang, Liu, and Schwarz, 2020; Avramov and Chordia, 2006).

Specifically, we follow Lewellen, Nagel, and Shanken (2010) and use portfolios formed on bond characteristics that are unrelated to the GDA5 factors. We consider the following eight sets of test portfolios and calculate the outstanding amount-weighted average excess return for each portfolio.

1. **25 Size/Maturity portfolios**: In each month, we independently sort bonds into 5 size and 5 maturity quintiles. We then take their intersection to form 5×5 portfolios.
2. **30 Fama-French industry portfolios**: In each month, we allocate bonds into portfolios based on the issuer's industry according to Fama-French 30 industry definitions.[9]
3. **25 Size/Rating portfolios**: Similar to the construction of the 25 Size/Maturity portfolios, we independently sort bonds into 5 size and 5 credit rating quintiles to form 25 portfolios.
4. **25 Credit Spread portfolios**: In each month, we sort bonds into 25 equal-sized portfolios based on their average credit spread in the past 12 months where the credit spread is defined as the bond yield to maturity minus the risk-free yield.[10]
5. **25 Rating/Maturity portfolios**: Similar to the 25 Size/Maturity portfolio, bonds are sorted independently into 5×5 portfolios based on their credit rating and maturity.
6. **27 Size/Rating/Maturity portfolios**: In each month, we form bond portfolios through an independent trivariate sort on bond size, credit rating, and maturity into three terciles, respectively. We then take their intersection to form $3 \times 3 \times 3 = 27$ portfolios.
7. **32 portfolios following Dickerson, Mueller, and Robotti (2023)**: 5 portfolios sorted on credit rating, 5 portfolios sorted on maturity, 10 portfolios sorted on credit spread, and 12 portfolios based on the Fama-French 12 industry definitions.
8. **35 portfolios following Elkamhi, Jo, and Nozawa (2024)**: 10 portfolios sorted on credit spread, 5 portfolios sorted on credit rating, 5 portfolios sorted on idiosyncratic volatility, 5 portfolios sorted on intermediary factor betas, 5 portfolios sorted on long-term reversal, and 5 portfolios sorted on maturity.[11]

[9] The definitions of the Fama-French 30 industries are based on SIC codes and retrieved from Kenneth French's website. For each bond in our sample, we first obtain its issuer SIC code from Mergent FISD. If it is unavailable, we retrieve the issuer's SIC code from CRSP based on its CUSIP.

[10] We use the overnight index swap (OIS) yield curve to proxy for the risk-free yield curve. Specifically, we download pricing data on OIS with different maturities from Bloomberg and bootstrap the corresponding zero yield curve. Finally, we use the OIS yield corresponding to the corporate bond's maturity date as the risk-free yield.

[11] Among the 40 portfolios of Elkamhi, Jo, and Nozawa (2024), we exclude 5 portfolios sorted on downside risk to avoid using portfolios sorted on a variable that is related to the GDA5 factors (Lewellen, Nagel, and Shanken, 2010).

Table 9 reports the results of the Fama-MacBeth two-pass regressions for each set of test portfolios independently. Our findings are mixed, since we find that our downside factors have significant prices of risk among three of the eight sets of portfolios.

In column (1) of Table 9, we use the 25 Size/Maturity portfolios. MKT, DS, and $MKTDS$ are significant at a 5% or higher significance level, while $VOLDS$ is significant at the 10% significance level. The intercept is insignificant. The results are similar in column (5), where we use the 25 Rating/Maturity portfolios. We find that three of five GDA5 factors are significant at a 5% or higher significance level, while the intercept is statistically insignificant. Similarly, in the regressions that use the 27 Size/Rating/Maturity portfolios in column (6), we find that three of five GDA5 factors are significant at a 10% or higher significance level, while the intercept is statistically insignificant.

In columns (2), (3) and (4), we use the 30 Fama-French industry portfolios, the 25 Size/Rating portfolios, and the 25 Credit Spread portfolios. For these test assets, the GDA5 factor model does not provide a good fit since none of the GDA5 factors have significant prices of risk.

In columns (7) and (8), we use the 32 portfolios formed by Dickerson, Mueller, and Robotti (2023) and the 35 portfolios formed by Elkamhi, Jo, and Nozawa (2024), respectively. In both estimations, only MKT has a significant price of risk at a 5% significance level while none of the other risk factors is significantly estimated.

To visualize the goodness of fit of the GDA5 model, we plot in Figure 4 the realized against the predicted mean excess returns for different sets of portfolios. These graphs are based on unconditional factor betas estimated using a time-series regression over the entire sample. We assume that the zero-beta excess return is zero and estimate without a constant. Other than for the 25 Size/Rating and 30 Fama-French industry portfolios, the GDA5 factor model provides a good fit.

By estimating the betas unconditionally over the entire sample period, we are essentially examining the OLS R^2 and suffer from the critique of Lewellen, Nagel, and Shanken (2010). We, therefore, repeat the analysis and estimate conditional factor betas using rolling windows of 36 months of data, as we do in Table 9. The corresponding illustrations in Figure 5 reflect the mixed results reported in Table 9, that is, the GDA5 factor model provides a good fit for the 25 Rating/Maturity, the 27 Size/Rating/Maturity portfolios, and the 35 Elkamhi, Jo, and Nozawa (2024) portfolios.

Dickerson, Mueller, and Robotti (2023) find that none of the BBW4, DEFTERM, CAPM, HKMSF, HKM, MACRO, HKMNT, LIQPS, LIQAM, VOLPS, and VOLAM models outperforms the simple bond CAPM in pricing the cross-section of corporate bond portfolio returns using their 32 test portfolios. These conclusions are based on model comparison techniques introduced by Kan, Robotti, and Shanken (2013). We implement, therefore, similar tests to assess whether the GDA5 factor model may outperform the bond CAPM.

Thus, Table 10 reports the results of the model comparisons of the GDA5, BBW4, STK5, BND5, HKM, DEFTERM, CAPM, HKMSF, MACRO, LIQPS, LIQAM, VOLPS, VOLAM, and HKMNT models versus the bond CAPM based on the GLS R^2 statistic from cross-sectional regressions as suggested by Lewellen, Nagel, and Shanken (2010). The test statistic used to compare models is the difference between each model's GLS R^2 and that of the bond CAPM, and the p-values are based on Wald tests under potential model misspecification (Kan, Robotti, and Shanken, 2013).

The first row of Table 10 suggests that the GDA5 model has a significantly higher GLS R^2 than the bond CAPM among five of the eight sets of portfolios. Specifically, in column (2), when using the 30 Fama-French industry portfolios, the GLS R^2 of the GDA5 model is higher than that of the bond CAPM by 0.175 in magnitude and it is significant at a 10% significance level. Similarly, in columns (3), (5), (7), and (8), when using the 25 Size/Rating portfolios, 25 Rating/Maturity portfolios, the 32 portfolios of Dickerson, Mueller, and Robotti (2023), and the 35 portfolios of Elkamhi, Jo, and Nozawa (2024), respectively, the GLS R^2 of the GDA5 model is higher than that of the bond CAPM by $0.102 \sim 0.351$ in magnitude and it is significant at a 5% or higher significance level. Across all sets of portfolios, the improvement of GLS R^2 over the bond CAPM for the GDA5 model ranges between 0.051 to 0.351.

While the GDA5 model shows significant improvement over the bond CAPM across most sets of test portfolios, the alternative models mostly fail to outperform the simple bond CAPM, consistent with Dickerson, Mueller, and Robotti (2023). An exception is the STK5 model, which significantly outperforms the bond CAPM using the 25 Size/Rating portfolios, and the BND5 model, which significantly outperforms the bond CAPM using the 25 Rating/Maturity portfolios.[12] However, their improvements in GLS R^2 are smaller in magnitude compared to the improvement obtained with the GDA5 factor model.

In summary, we find that the significance of the prices of risk of the GDA5 model depends on the choice of test portfolios. The GDA5 model has significant prices of risk and provides a reasonably good fit for three of the eight sets of portfolios that we examine. In addition, we find that the GDA5 model shows statistically significant improvement over the bond CAPM in five of the eight sets of portfolios, while alternative models fail to outperform the bond CAPM for virtually all sets of test assets.

5 Conclusion

We test the ability of theory-motivated risk factors to explain the cross-section of corporate bond returns. In an intertemporal equilibrium asset pricing model with disappointment aversion preferences and time-varying macroeconomic uncertainty, a linear factor representation emerges where

[12] Dickerson, Mueller, and Robotti (2023) do not examine STK5 and BND5 factor models.

expected excess returns command risk premiums for their return covariation with five risk factors, including the market, the volatility, and three downside risk factors.

Our model is a natural candidate for the cross-section of corporate bond returns. Due to their concave payoff functions, fixed income securities are particularly sensitive to downside risk. This is well captured in dynamic models with asymmetric preferences that can endogenously generate time-varying risk premiums associated with disappointing states. Moreover, an extensive literature documents the importance of volatility risk for asset prices, including corporate bond returns (e.g., Chung, Wang, and Wu, 2019; Bali, Subrahmanyam, and Wen, 2021b).

We test the model using individual bonds as test assets because the factor structure of corporate bonds is significantly stronger than that of equities and because of the apparent information loss and reduction in the dispersion of beta estimates. We find that all factors carry theoretically consistent signs and are significantly priced, except for the volatility factor, which is only marginally significant. Thus, we complement and extend the findings in Chung, Wang, and Wu (2019) by providing a theoretical foundation for volatility risk in the cross-section of corporate bond returns and by showing that volatility downside risk is more informative than unconditional volatility risk.

For comparison with the literature, we also examine the ability of our model to explain the cross-section of corporate bond portfolios. We find that our model provides a good fit for three of the eight sets of test portfolios. We confirm the results of Dickerson, Mueller, and Robotti (2023) that existing empirical factor models fail to outperform the bond CAPM, but show that our model improves the cross-sectional explanatory power for excess returns over the bond CAPM in five of the eight sets of test portfolios.

Our work contributes to the ongoing search for theory-motivated risk factors in the cross-section of corporate bond returns. The contrasting asset pricing results when using bonds or portfolios as test assets underscores the impact that information loss can have on model assessment when portfolios are prioritized over individual securities for explaining the cross-section of corporate bond returns.

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Table 1: Descriptive Statistics

This table reports time-series averages of cross-sectional descriptive statistics for variables in our monthly corporate bond sample. The bond excess return is defined as the monthly bond return minus the one-month Treasury bill rate. The duration-adjusted return is the monthly bond return minus a duration-matched Treasury return following van Binsbergen, Nozawa, and Schwert (2024). Rating is the average corporate bond credit rating from S&P Global Ratings and Moody's, coded on a numerical scale ranging from AAA=1 to D=22 for S&P and from Aaa=1 to C=21 for Moody's. If either credit rating is missing, we use only one of both ratings. Maturity is defined as the number of years until the bond's maturity date. Bond size is the amount outstanding in million USD. BPW illiq is the monthly bond illiquidity measure of Bao, Pan, and Wang (2011) and DFL illiq is the monthly bond illiquidity measure (λ) of Dick-Nielsen, Feldhütter, and Lando (2012). To reduce the impact of missing values for these variables, we supplement for each bond and each month, missing illiquidity values with the average monthly illiquidity over the past 12 months. Coupon is the bond's coupon rate in percentage points. Bond age is the number of years from the bond's offering date. The 5% Value-at-Risk (5% VaR) is calculated following Bai, Bali, and Wen (2019). # Inst. defines the number of institutional investors and % IO is the percentage of the bond issuer's equity shares owned by institutional investors. # Analysts is the number of analysts forecasting the issuers' earnings per share and Forecast Disp. is the standard deviation of the most recent quarterly forecast scaled by the absolute mean forecast. Stock excess return is the issuers' stock return minus the one-month Treasury bill rate. For each variable, we report the number of observations (N), the mean, median, standard deviation (SD) and the 1st, 5th, 25th, 75th, 95th and 99th percentiles of the distribution. Bond transaction data are from TRACE. Other bond-level data are from Mergent FISD. Institutional ownership data are from Thomson-Reuters 13F and analyst data are from I/B/E/S. Stock return data are from CRSP. Table A.1 provides detailed variable definitions. The sample period spans from July 2002 to December 2021.

					Percentiles					
	N	Mean	Median	SD	1	5	25	75	95	99
Bond excess return (%)	1,263,743	0.59	0.40	3.84	−8.00	−3.68	−0.69	1.63	5.33	11.37
Duration-adjusted return (%)	1,263,743	0.33	0.18	3.82	−8.19	−3.88	−0.91	1.34	4.98	11.01
Rating	1,236,724	8.65	8.04	3.82	1.42	3.02	6.09	10.50	15.97	19.16
Maturity	1,263,743	9.69	6.55	8.91	1.11	1.55	3.65	12.73	27.34	30.88
Bond size (million $)	1,263,743	542.32	381.50	596.55	3.34	11.93	189.34	677.35	1651.73	2868.15
BPW illiq	906,445	1.02	0.20	5.05	−1.21	−0.14	0.03	0.76	4.10	13.81
DFL illiq	1,099,505	0.38	−0.46	2.75	−2.16	−1.97	−1.37	1.28	5.32	9.55
Coupon (%)	1,263,743	5.65	5.52	1.71	2.03	3.10	4.56	6.60	8.69	10.36
Bond age	1,263,743	4.60	3.41	4.41	0.07	0.33	1.59	6.17	14.16	19.88
5% VaR (%)	599,130	4.55	3.18	4.39	0.59	0.92	1.88	5.61	12.71	21.57
# Inst.	938,784	830.99	718.98	512.96	66.12	148.32	431.77	1186.04	1809.03	1985.76
% IO	899,025	0.66	0.68	0.19	0.20	0.31	0.53	0.80	0.93	0.97
# Analysts	1,016,155	12.26	11.99	6.68	0.50	1.96	7.21	16.96	23.32	29.03
Forecast Disp.	978,768	0.32	0.04	2.54	0.00	0.01	0.02	0.10	1.62	3.55
Stock excess return (%)	1,051,676	0.81	0.60	8.56	−19.84	−11.09	−3.55	4.83	13.45	24.30

Table 2: Correlation Matrix of Betas and Bond Characteristics

This table reports the time-series average of pair-wise cross-sectional correlation coefficients for the GDA5 factor betas and a range of bond characteristics including bond coupon, maturity, rating, issuance size, age, 5% Value-at-Risk (VaR5), the illiquidity measures of Bao, Pan, and Wang (2011) (BPW illiq) and Dick-Nielsen, Feldhütter, and Lando (2012) (DFL illiq), lagged bond return, number of institutional investors, percentage equity ownership of institutional ownership, number of analysts, earnings forecast dispersion, and contemporanous stock excess return. Specifically, for each month we calculate the pair-wise cross-sectional correlation coefficients among these variables. Then, we take their time-series average and report in the table. MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. Table A.1 provides details for all variable definitions. Factor betas are estimated using rolling windows of lagged 36 months and requiring a minimum of 24 observations. The sample period spans July 2002 to December 2021. Numbers in bold with a * indicate statistical significance at the 1% level computed using the t test.

	β_{MKT}	β_{DS}	β_{MKTDS}	β_{VOL}	β_{VOLDS}	Coupon	Maturity	Rating	Bond size	Bond age	VaR5	BPW illiq	DFL illiq	Lagged return	# Inst.	% IO	# Analysts	Forecast Disp.	Stock excess return
β_{MKT}		$\mathbf{0.15}^*$	$\mathbf{-0.41}^*$	-0.03	$\mathbf{0.10}^*$	$\mathbf{0.09}^*$	$\mathbf{0.35}^*$	$\mathbf{0.11}^*$	0.02	-0.00	$\mathbf{0.41}^*$	$\mathbf{0.07}^*$	$\mathbf{0.17}^*$	0.05	-0.01	$\mathbf{-0.02}^*$	$\mathbf{0.02}^*$	$\mathbf{0.02}^*$	0.00
β_{DS}			$\mathbf{0.47}^*$	$\mathbf{-0.09}^*$	$\mathbf{-0.23}^*$	-0.01	-0.02	0.01	$\mathbf{-0.05}^*$	$\mathbf{-0.02}^*$	0.04	$\mathbf{0.03}^*$	$\mathbf{0.04}^*$	-0.00	-0.02	$\mathbf{0.03}^*$	$\mathbf{-0.04}^*$	-0.01	0.02
β_{MKTDS}				-0.02	$\mathbf{-0.10}^*$	-0.02	-0.02	-0.02	-0.01	-0.01	-0.02	$\mathbf{0.03}^*$	$\mathbf{0.04}^*$	0.00	0.00	0.00	-0.00	$\mathbf{0.03}^*$	0.01
β_{VOL}					$\mathbf{-0.46}^*$	$\mathbf{-0.11}^*$	$\mathbf{0.12}^*$	$\mathbf{-0.25}^*$	$\mathbf{0.01}^*$	$\mathbf{0.02}^*$	$\mathbf{-0.15}^*$	$\mathbf{-0.03}^*$	$\mathbf{-0.03}^*$	-0.01	$\mathbf{0.11}^*$	0.00	0.01	$\mathbf{-0.07}^*$	0.02
β_{VOLDS}						$\mathbf{-0.05}^*$	-0.00	-0.02	$\mathbf{0.02}^*$	$\mathbf{-0.01}^*$	0.00	-0.02	-0.02	0.02	$\mathbf{0.06}^*$	$\mathbf{-0.01}^*$	$\mathbf{0.05}^*$	-0.01	-0.01
Coupon							$\mathbf{0.12}^*$	$\mathbf{0.53}^*$	$\mathbf{-0.08}^*$	$\mathbf{0.38}^*$	$\mathbf{0.28}^*$	$\mathbf{0.08}^*$	$\mathbf{0.13}^*$	$\mathbf{0.04}^*$	$\mathbf{-0.30}^*$	$\mathbf{0.05}^*$	$\mathbf{-0.13}^*$	$\mathbf{0.08}^*$	0.00
Maturity								$\mathbf{-0.15}^*$	$\mathbf{-0.01}^*$	$\mathbf{0.05}^*$	$\mathbf{0.25}^*$	$\mathbf{0.10}^*$	$\mathbf{0.26}^*$	0.04	$\mathbf{0.12}^*$	$\mathbf{-0.04}^*$	$\mathbf{0.07}^*$	$\mathbf{-0.03}^*$	0.00
Rating									$\mathbf{-0.11}^*$	$\mathbf{0.03}^*$	$\mathbf{0.49}^*$	$\mathbf{0.12}^*$	$\mathbf{0.09}^*$	$\mathbf{0.06}^*$	$\mathbf{-0.70}^*$	$\mathbf{0.26}^*$	$\mathbf{-0.21}^*$	$\mathbf{0.15}^*$	0.01
Bond size										$\mathbf{-0.17}^*$	$\mathbf{-0.10}^*$	$\mathbf{-0.14}^*$	$\mathbf{-0.27}^*$	$\mathbf{-0.02}^*$	$\mathbf{0.21}^*$	$\mathbf{-0.08}^*$	$\mathbf{0.20}^*$	$\mathbf{-0.01}^*$	0.00
Bond age											$\mathbf{0.07}^*$	$\mathbf{0.12}^*$	$\mathbf{0.22}^*$	$\mathbf{0.02}^*$	$\mathbf{0.03}^*$	$\mathbf{-0.04}^*$	$\mathbf{0.01}^*$	$\mathbf{0.01}^*$	0.00
VaR5												$\mathbf{0.28}^*$	$\mathbf{0.41}^*$	0.06	$\mathbf{-0.19}^*$	$\mathbf{-0.06}^*$	$\mathbf{-0.06}^*$	$\mathbf{0.14}^*$	-0.01
BPW illiq													$\mathbf{0.32}^*$	0.00	$\mathbf{-0.03}^*$	$\mathbf{-0.05}^*$	$\mathbf{-0.05}^*$	$\mathbf{0.03}^*$	-0.01
DFL illiq														0.03	$\mathbf{0.05}^*$	$\mathbf{-0.14}^*$	-0.00	$\mathbf{0.04}^*$	-0.02
Lagged return															-0.03	-0.01	$\mathbf{-0.02}^*$	-0.01	0.02
# Inst.																$\mathbf{-0.40}^*$	$\mathbf{0.33}^*$	$\mathbf{-0.09}^*$	-0.01
% IO																	$\mathbf{-0.05}^*$	0.01	0.02
# Analysts																		-0.00	-0.01
Forecast Disp.																			-0.02
Stock excess return																			

Table 3: Bond-level Fama-MacBeth Regressions

This table reports the results of the Fama-MacBeth two-pass regressions of individual bond excess returns on the GDA5 factors. MKT is the market return minus the one-month Treasury rate. We use four different proxies for the market return. In column (1), the market return is the outstanding amount-weighted average return of all bonds in our sample. In column (2), the market return is the return of the Merrill Lynch U.S. Corporate Master Index obtained from Eikon (ticker: `.MERC0A0`). In column (3), the market return is the Barclays U.S. Corporate Total Return Index obtained from Bloomberg (ticker: `LUACTRUU Index`). In column (4), the market return is the CRSP value-weighted total return obtained from CRSP in WRDS (file: `DSI`). VOL is the monthly change in variance based on the VIX index obtained from Cboe Global Markets. DS is the downside factor constructed. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. Factor betas are estimated using rolling windows with a lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 are reported at the bottom. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans July 2002 to December 2021.

	(1) Sample bond market	(2) ML Corporate	(3) Barclays Corporate	(4) CRSP
β_{MKT}	0.352**	0.182**	0.200**	0.782*
	(2.50)	(2.03)	(2.30)	(1.81)
β_{DS}	−13.190**	−10.921***	−9.382*	−8.537*
	(−2.29)	(−2.70)	(−1.86)	(−1.91)
β_{MKTDS}	0.253***	0.193***	0.188**	0.574**
	(2.96)	(2.90)	(2.46)	(2.50)
β_{VOL}	−0.019	−0.028*	−0.027	−0.021*
	(−1.11)	(−1.68)	(−1.50)	(−1.86)
β_{VOLDS}	−0.034**	−0.032**	−0.035**	−0.023*
	(−2.13)	(−2.34)	(−2.35)	(−1.96)
Constant	0.108	0.301**	0.241**	0.284**
	(1.14)	(2.56)	(2.35)	(2.34)
N	578,841	578,057	578,354	574,548
Adjusted R^2	0.148	0.144	0.143	0.134

Table 4: Factor Correlations

This table reports pairwise time-series correlation coefficients between monthly risk factors. MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample, minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. DRF, LRF, and CRF are the downside risk, liquidity risk, and credit risk factors, respectively, constructed following Bai, Bali, and Wen (2019). $MKTS$, SMB, and HML are the Fama and French (1993) three factors and UMD is the Carhart (1997) stock momentum factor. Data on these four factors are obtained from Kenneth French's website. $LIQS$ is the Pástor and Stambaugh (2003) stock liquidity factor. Data on $LIQS$ is obtained from Lubos Pastor's website. DEF is the difference between long-term corporate bond and long-term government bond returns and $TERM$ is the difference between long-term government bond returns and the 1-month Treasury rate. Data on these two factors are obtained from Amit Goyal's website. $MOMB$ is the bond momentum factor constructed following Jostova, Nikolova, Philipov, and Stahel (2013). $LIQBPS$ ($LIQBAM$) is the Pastor-Stambaugh (Amihud) bond liquidity factor constructed following Lin, Wang, and Wu (2011) and $LIQB$ is the traded factor of $LIQBPS$ constructed following Lin, Wang, and Wu (2011) and Bai, Bali, and Wen (2019). $CPTL$ and $CPTLT$ are the non-traded and traded intermediary risk factors, respectively from He, Kelly, and Manela (2017). Data on the two factors are downloaded from Zhiguo He's website. ΔUNC is the monthly change of the economic uncertainty index downloaded from Sydney Ludvigson's website and ΔVIX is the first difference of the end-of-month VIX index downloaded from Cboe Global Markets. Table A.1 provides detailed variable definitions. The sample period spans from July 2002 to December 2021. Numbers in bold with an * indicate statistical significance at the 1% level.

	MKT	DS	$MKTDS$	VOL	$VOLDS$	DRF	LRF	CRF	$MKTS$	SMB	HML	UMD	$LIQS$	DEF	$TERM$	$MOMB$	$LIQB$	$CPTLT$	ΔUNC	$LIQBPS$	$LIQBAM$	ΔVIX	$CPTL$
MKT		$\mathbf{-0.55}^*$	$\mathbf{0.69}^*$	$\mathbf{-0.59}^*$	$\mathbf{-0.44}^*$	$\mathbf{0.83}^*$	$\mathbf{0.72}^*$	$\mathbf{0.44}^*$	$\mathbf{0.48}^*$	0.16	0.05	$\mathbf{-0.37}^*$	0.15	$\mathbf{0.59}^*$	$\mathbf{0.27}^*$	$\mathbf{-0.36}^*$	$\mathbf{-0.39}^*$	$\mathbf{0.37}^*$	$\mathbf{-0.37}^*$	$\mathbf{-0.38}^*$	$\mathbf{0.47}^*$	$\mathbf{-0.51}^*$	$\mathbf{0.32}^*$
DS			$\mathbf{-0.52}^*$	$\mathbf{0.47}^*$	$\mathbf{0.51}^*$	$\mathbf{-0.48}^*$	$\mathbf{-0.36}^*$	$\mathbf{-0.21}^*$	$\mathbf{-0.51}^*$	−0.11	−0.07	$\mathbf{0.17}^*$	−0.05	$\mathbf{-0.35}^*$	$\mathbf{-0.17}^*$	0.10	0.13	$\mathbf{-0.41}^*$	0.16	−0.00	$\mathbf{-0.24}^*$	$\mathbf{0.55}^*$	$\mathbf{-0.34}^*$
$MKTDS$				$\mathbf{-0.45}^*$	$\mathbf{-0.55}^*$	$\mathbf{0.50}^*$	$\mathbf{0.41}^*$	$\mathbf{0.30}^*$	$\mathbf{0.40}^*$	0.09	0.06	−0.15	$\mathbf{0.29}^*$	$\mathbf{0.46}^*$	0.13	$\mathbf{-0.18}^*$	0.00	$\mathbf{0.28}^*$	$\mathbf{-0.41}^*$	−0.12	$\mathbf{0.66}^*$	$\mathbf{-0.40}^*$	$\mathbf{0.25}^*$
VOL					$\mathbf{0.76}^*$	$\mathbf{-0.44}^*$	$\mathbf{-0.35}^*$	$\mathbf{-0.43}^*$	$\mathbf{-0.72}^*$	$\mathbf{-0.20}^*$	−0.15	$\mathbf{0.31}^*$	$\mathbf{-0.22}^*$	$\mathbf{-0.51}^*$	0.07	0.14	0.16	$\mathbf{-0.57}^*$	$\mathbf{0.34}^*$	$\mathbf{0.30}^*$	$\mathbf{-0.40}^*$	$\mathbf{0.94}^*$	$\mathbf{-0.50}^*$
$VOLDS$						$\mathbf{-0.22}^*$	−0.17	$\mathbf{-0.37}^*$	$\mathbf{-0.59}^*$	−0.14	−0.17	0.16	$\mathbf{-0.24}^*$	$\mathbf{-0.38}^*$	0.07	−0.03	−0.17	$\mathbf{-0.49}^*$	$\mathbf{0.44}^*$	0.06	$\mathbf{-0.52}^*$	$\mathbf{0.70}^*$	$\mathbf{-0.45}^*$
DRF							$\mathbf{0.81}^*$	$\mathbf{0.41}^*$	$\mathbf{0.47}^*$	0.14	0.06	$\mathbf{-0.40}^*$	0.09	$\mathbf{0.68}^*$	0.04	$\mathbf{-0.57}^*$	$\mathbf{-0.62}^*$	$\mathbf{0.39}^*$	$\mathbf{-0.30}^*$	$\mathbf{-0.35}^*$	$\mathbf{0.30}^*$	$\mathbf{-0.44}^*$	$\mathbf{0.34}^*$
LRF								$\mathbf{0.36}^*$	$\mathbf{0.28}^*$	0.09	0.01	$\mathbf{-0.32}^*$	0.04	$\mathbf{0.44}^*$	0.14	$\mathbf{-0.53}^*$	$\mathbf{-0.59}^*$	$\mathbf{0.23}^*$	$\mathbf{-0.23}^*$	$\mathbf{-0.34}^*$	$\mathbf{0.28}^*$	$\mathbf{-0.31}^*$	$\mathbf{0.17}^*$
CRF									$\mathbf{0.61}^*$	$\mathbf{0.38}^*$	$\mathbf{0.30}^*$	$\mathbf{-0.50}^*$	$\mathbf{0.21}^*$	$\mathbf{0.51}^*$	$\mathbf{-0.53}^*$	$\mathbf{-0.34}^*$	−0.18	$\mathbf{0.61}^*$	$\mathbf{-0.35}^*$	−0.15	$\mathbf{0.43}^*$	$\mathbf{-0.41}^*$	$\mathbf{0.63}^*$
$MKTS$										$\mathbf{0.35}^*$	$\mathbf{0.22}^*$	$\mathbf{-0.41}^*$	$\mathbf{0.23}^*$	$\mathbf{0.56}^*$	$\mathbf{-0.30}^*$	$\mathbf{-0.19}^*$	−0.12	$\mathbf{0.83}^*$	$\mathbf{-0.30}^*$	0.02	$\mathbf{0.33}^*$	$\mathbf{-0.76}^*$	$\mathbf{0.77}^*$
SMB											0.17	−0.16	$\mathbf{0.21}^*$	$\mathbf{0.25}^*$	$\mathbf{-0.26}^*$	−0.16	−0.04	$\mathbf{0.26}^*$	−0.09	−0.02	$\mathbf{0.17}^*$	$\mathbf{-0.20}^*$	$\mathbf{0.26}^*$
HML												$\mathbf{-0.37}^*$	$\mathbf{-0.19}^*$	$\mathbf{0.20}^*$	$\mathbf{-0.23}^*$	0.06	−0.02	$\mathbf{0.51}^*$	$\mathbf{-0.17}^*$	0.04	0.08	−0.12	$\mathbf{0.48}^*$
UMD													0.12	$\mathbf{-0.34}^*$	$\mathbf{0.21}^*$	$\mathbf{0.33}^*$	$\mathbf{0.29}^*$	$\mathbf{-0.59}^*$	$\mathbf{0.19}^*$	0.03	−0.16	$\mathbf{0.29}^*$	$\mathbf{-0.57}^*$
$LIQS$														$\mathbf{0.24}^*$	$\mathbf{-0.19}^*$	−0.04	0.16	0.08	−0.10	0.09	$\mathbf{0.36}^*$	$\mathbf{-0.18}^*$	0.09
DEF															$\mathbf{-0.45}^*$	$\mathbf{-0.43}^*$	$\mathbf{-0.25}^*$	$\mathbf{0.56}^*$	$\mathbf{-0.34}^*$	$\mathbf{-0.32}^*$	$\mathbf{0.50}^*$	$\mathbf{-0.52}^*$	$\mathbf{0.54}^*$
$TERM$																$\mathbf{0.28}^*$	−0.08	$\mathbf{-0.40}^*$	0.08	−0.10	$\mathbf{-0.21}^*$	0.15	$\mathbf{-0.44}^*$
$MOMB$																	$\mathbf{0.56}^*$	$\mathbf{-0.17}^*$	0.13	$\mathbf{0.26}^*$	−0.13	$\mathbf{0.19}^*$	−0.15
$LIQB$																		−0.12	−0.03	$\mathbf{0.47}^*$	0.14	0.16	−0.04
$CPTLT$																			$\mathbf{-0.28}^*$	0.06	$\mathbf{0.26}^*$	$\mathbf{-0.60}^*$	$\mathbf{0.94}^*$
ΔUNC																				0.08	$\mathbf{-0.42}^*$	$\mathbf{0.29}^*$	$\mathbf{-0.29}^*$
$LIQBPS$																					$\mathbf{-0.21}^*$	$\mathbf{0.20}^*$	0.08
$LIQBAM$																						$\mathbf{-0.31}^*$	$\mathbf{0.28}^*$
ΔVIX																							$\mathbf{-0.53}^*$
$CPTL$																							

Table 5: Bond-level Fama-MacBeth Regressions: Alternative Traded Factors

This table reports the results of the Fama-MacBeth two-pass regressions of individual bond excess returns on the GDA5 factors controlling for traded factors. In the GDA5 model, MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. For each factor model, all factor betas are jointly estimated using rolling windows with a lag of 36 months and requiring a minimum of 24 observations. In column (2), we control for the BBW4 factors (DRF, LRF, and CRF) of Bai, Bali, and Wen (2019). In column (3), we control for the STK5 factors ($MKTS$, SMB, HML, UMD, and $LIQS$) of Bai, Bali, and Wen (2019). In column (4), we control for the BND5 factor betas (DEF, $TERM$, $MOMB$, $LIQB$) of Bai, Bali, and Wen (2019). In column (5), we control for the HKM factors ($MKTS$ and $CPTLT$) of He, Kelly, and Manela (2017). In column (6), we control for the DEFTERM factors (DEF and $TERM$) of Dickerson, Mueller, and Robotti (2023). In column (7), we control for the stock CAPM ($MKTS$) of Dickerson, Mueller, and Robotti (2023). In column (8), we control for HKMSF single factor $CPTLT$ of Dickerson, Mueller, and Robotti (2023). We exclude the bond market beta from BBW4 and BND5 to avoid potential multicollinearity issues in our regressions. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{MKT}	0.352**	0.344***	0.174*	0.329***	0.245***	−0.001	0.167	0.197*
	(2.50)	(3.12)	(1.85)	(3.50)	(2.73)	(−0.01)	(1.54)	(1.92)
β_{DS}	−13.190**	−15.084***	−9.810**	−11.918***	−12.063***	−9.921*	−11.029***	−10.225***
	(−2.29)	(−3.58)	(−2.54)	(−4.40)	(−3.26)	(−1.75)	(−2.84)	(−2.74)
β_{MKTDS}	0.253***	0.222***	0.171***	0.211***	0.162***	0.133	0.168***	0.183***
	(2.96)	(2.96)	(3.09)	(4.25)	(3.16)	(1.59)	(2.80)	(2.95)
β_{VOL}	−0.019	−0.055***	−0.015	−0.055***	−0.021	−0.015*	−0.003	−0.008
	(−1.11)	(−3.97)	(−1.41)	(−2.88)	(−1.32)	(−1.76)	(−0.25)	(−0.76)
β_{VOLDS}	−0.034**	−0.040***	−0.022**	−0.040**	−0.020**	−0.026***	−0.021**	−0.019**
	(−2.13)	(−3.48)	(−2.30)	(−2.48)	(−1.97)	(−2.69)	(−2.54)	(−2.42)
β_{DRF}		0.046						
		(0.38)						
β_{LRF}		0.002						
		(0.04)						
β_{CRF}		−0.160						
		(−0.67)						
β_{MKTS}			0.229		−0.087		0.252	
			(0.46)		(−0.17)		(0.43)	
β_{SMB}			−0.100					
			(−0.52)					
β_{HML}			−0.138					
			(−0.73)					
β_{UMD}			−0.181					
			(−0.68)					
β_{LIQS}			0.018					
			(0.74)					
β_{DEF}				−0.161		0.065		
				(−1.19)		(0.38)		
β_{TERM}				0.370		0.518		
				(1.28)		(1.28)		
β_{MOMB}				−0.030				
				(−0.24)				
β_{LIQB}				0.023				
				(0.15)				
β_{CPTLT}					0.254			0.372
					(0.34)			(0.49)
Constant	0.108	0.158	0.127	0.189***	0.151*	0.118	0.118	0.137
	(1.14)	(1.47)	(1.54)	(3.29)	(1.93)	(1.30)	(1.29)	(1.55)
N	578,841	549,016	578,841	475,287	578,841	578,841	578,841	578,841
Adjusted R^2	0.148	0.199	0.200	0.193	0.178	0.185	0.169	0.168

Table 6: Bond-level Fama-MacBeth Regressions: Alternative Non-traded Factors

This table reports the results of the Fama-MacBeth two-pass regressions of individual bond excess returns on the GDA5 factors controlling for non-traded factors. In the GDA5 model, MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. For each factor model, all factor betas are estimated jointly using rolling windows with a lag of 36 months and requiring a minimum of 24 observations. Column (1) reports our main results from Table 3. In column (2), we control for MACRO factors $MKTB$ and ΔUNC as in Bali, Subrahmanyam, and Wen (2021b). In column (3), we control for LIQPS factors ($MKTS$, SMB, HML, DEF, $TERM$ and $LIQBPS$) as in Lin, Wang, and Wu (2011). In column (4), we control for LIQAM factors ($MKTS$, SMB, HML, DEF, $TERM$ and $LIQBAM$) as in Lin, Wang, and Wu (2011). In column (5), we control for VOLPS factors ($MKTS$, SMB, HML, DEF, $TERM$, $LIQBPS$, and ΔVIX) as in Chung, Wang, and Wu (2019). In column (6), we control for VOLAM factors ($MKTS$, SMB, HML, DEF, $TERM$, $LIQBAM$, and ΔVIX) as in Chung, Wang, and Wu (2019). In column (7), we control for the HKMNT factors ($MKTS$ and $CPTL$) as in He, Kelly, and Manela (2017). All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_{MKT}	0.352^{**}	0.341^{**}	-0.079	-0.037	-0.101	-0.102	0.245^{**}
	(2.50)	(2.50)	(-0.56)	(-0.32)	(-0.75)	(-0.84)	(2.48)
β_{DS}	-13.190^{**}	-13.669^{**}	-7.395^{**}	-5.937^{*}	-7.469^{**}	-5.139	-12.915^{***}
	(-2.29)	(-2.57)	(-2.09)	(-1.68)	(-2.42)	(-1.65)	(-3.10)
β_{MKTDS}	0.253^{***}	0.219^{***}	0.087^{*}	0.098^{*}	0.091^{**}	0.082^{*}	0.164^{***}
	(2.96)	(2.76)	(1.78)	(1.90)	(2.01)	(1.80)	(2.68)
β_{VOL}	-0.019	-0.018	-0.004	-0.013	-0.020^{**}	-0.017	-0.024
	(-1.11)	(-1.20)	(-0.34)	(-1.21)	(-2.27)	(-1.47)	(-1.47)
β_{VOLDS}	-0.034^{**}	-0.026^{**}	-0.018^{***}	-0.022^{**}	-0.024^{***}	-0.020^{***}	-0.023^{**}
	(-2.13)	(-2.18)	(-2.73)	(-2.56)	(-3.06)	(-2.92)	(-2.41)
β_{UNC}		-0.136					
		(-0.65)					
β_{MKTS}			0.436	0.302	0.223	0.251	-0.140
			(0.78)	(0.56)	(0.47)	(0.51)	(-0.26)
β_{SMB}			-0.123	-0.121	-0.214	-0.186	
			(-0.58)	(-0.52)	(-1.13)	(-0.92)	
β_{HML}			-0.094	-0.138	-0.172	-0.168	
			(-0.33)	(-0.48)	(-0.61)	(-0.58)	
β_{DEF}			0.157	0.104	0.112	0.099	
			(0.84)	(0.59)	(0.67)	(0.58)	
β_{TERM}			0.377	0.487	0.501	0.619^{**}	
			(1.24)	(1.64)	(1.59)	(2.13)	
β_{LIQBPS}			-0.008		0.093		
			(-0.01)		(0.16)		
β_{LIQBAM}				0.792^{*}		0.842^{*}	
				(1.72)		(1.93)	
β_{VIX}					17.685	2.812	
					(0.40)	(0.05)	
β_{CPTL}							0.109
							(0.16)
Constant	0.108	0.123	0.119	0.102	0.131	0.108	0.133
	(1.14)	(1.31)	(1.27)	(1.13)	(1.36)	(1.16)	(1.61)
N	578,841	578,841	578,788	578,788	578,788	578,788	578,841
Adjusted R^2	0.148	0.161	0.213	0.212	0.219	0.217	0.176

Table 7: Bond-level Fama-MacBeth Regressions: Robustness Tests

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factors. MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. In column (1), the duration-adjusted return is used as the dependent variable following van Binsbergen, Nozawa, and Schwert 2024 based on Treasury yield data from Gürkaynak, Brian Sack, and Wright (2007). In column (2), we use the excess return winsorized at the 1% and 99% level over the whole sample as the dependent variable. In column (3), we do not winsorize factor betas in each cross-section. Factor betas are estimated using rolling windows with a lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) Duration-adjusted return	(2) Winsorized return	(3) Beta not winsorized
β_{MKT}	0.297**	0.296***	0.358**
	(1.97)	(2.78)	(2.41)
β_{DS}	−12.882**	−9.163**	−14.090**
	(−2.16)	(−2.42)	(−2.25)
β_{MKTDS}	0.232**	0.162**	0.273***
	(2.55)	(2.58)	(2.94)
β_{VOL}	−0.020	−0.032**	−0.022
	(−1.25)	(−2.33)	(−1.52)
β_{VOLDS}	−0.033**	−0.036***	−0.037***
	(−2.14)	(−2.72)	(−2.62)
Constant	−0.042	0.201***	0.098
	(−0.41)	(3.24)	(1.04)
N	578,841	578,841	578,841
Adjusted R^2	0.127	0.160	0.149

Table 8: Bond-level Fama-MacBeth Regressions: Controlling for Bond and Issuer Characteristics

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factors controlling for bond characteristics. MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. In column (1), we report the baseline GDA5 model. In columns (2)-(15), we successively control one by one for bond size, maturity, rating, coupon, VaR5, bond age, BPW illiquidity, DFL illiquidity, lagged bond return, number of institutional investors, percentage of institutional equity ownership, number of analysts, earnings forecast dispersion, and contemporaneous stock excess return. In column (16), we control for all of the bond and issuer characteristics together. Factor betas are estimated in rolling windows using a lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
β_{MKT}	0.352**	0.343***	0.303**	0.285**	0.349**	0.165	0.351**	0.324**	0.300**	0.386***	0.237**	0.246**	0.253**	0.261**	0.236**	0.093
	(2.50)	(2.64)	(2.05)	(2.42)	(2.50)	(1.34)	(2.50)	(2.52)	(2.56)	(2.62)	(2.01)	(1.99)	(1.99)	(2.06)	(2.27)	(0.89)
β_{DS}	−13.190**	−12.672**	−13.010**	−12.444**	−13.381**	−7.680*	−13.055**	−12.500**	−11.907**	−13.894**	−5.642	−5.508	−6.515	−6.055	−6.099	−3.056
	(−2.29)	(−2.32)	(−2.17)	(−2.41)	(−2.35)	(−1.68)	(−2.27)	(−2.28)	(−2.40)	(−2.52)	(−1.14)	(−1.13)	(−1.30)	(−1.21)	(−1.41)	(−0.99)
β_{MKTDS}	0.253***	0.249***	0.240***	0.220***	0.250***	0.164**	0.251***	0.229***	0.223***	0.261***	0.156**	0.156**	0.164**	0.159**	0.160**	0.102*
	(2.96)	(3.14)	(2.67)	(2.94)	(2.93)	(2.10)	(2.94)	(3.06)	(3.04)	(3.16)	(2.32)	(2.19)	(2.12)	(2.11)	(2.58)	(1.73)
β_{VOL}	−0.019	−0.018	−0.021	−0.018	−0.019	−0.009	−0.019	−0.014	−0.018	−0.022	−0.016	−0.015	−0.014	−0.018	−0.017	−0.033*
	(−1.11)	(−1.07)	(−1.27)	(−1.41)	(−1.24)	(−0.86)	(−1.12)	(−0.74)	(−1.08)	(−1.23)	(−1.01)	(−0.83)	(−0.82)	(−1.13)	(−1.16)	(−1.78)
β_{VOLDS}	−0.034**	−0.033**	−0.035**	−0.030**	−0.034**	−0.024**	−0.034**	−0.031*	−0.032**	−0.040**	−0.030*	−0.031*	−0.030*	−0.032*	−0.030**	−0.043**
	(−2.13)	(−2.10)	(−2.23)	(−2.18)	(−2.19)	(−2.22)	(−2.13)	(−1.79)	(−2.08)	(−2.37)	(−1.82)	(−1.74)	(−1.81)	(−1.96)	(−1.99)	(−2.16)
ln(Bond size)		−0.065														0.042*
		(−1.31)														(1.77)
Maturity			0.004													0.006
			(0.56)													(0.90)
Rating				0.031												0.019
				(1.16)												(1.06)
Coupon					0.029											−0.005
					(0.87)											(−0.46)
VaR5						5.009										5.157*
						(1.31)										(1.96)
Bond age							0.007									0.001
							(1.51)									(0.33)
BPW illiq								0.031								0.028
								(0.76)								(1.25)
DFL illiq									0.044							0.017
									(1.61)							(1.17)
Lagged return										−8.033***						−20.476***
										(−3.77)						(−9.64)
# Inst.											−0.000					0.000
											(−0.71)					(1.29)
% IO												−0.261*				−0.026
												(−1.75)				(−0.21)
# Analysts													−0.007			−0.006***
													(−1.61)			(−2.71)
Forecast Disp.														−0.150*		−0.096*
														(−1.67)		(−1.97)
Stock excess return															6.732***	5.471***
															(10.78)	(10.10)
Constant	0.108	0.505	0.115	−0.117	−0.083	0.013	0.070	0.090	0.115	0.127	0.220**	0.366***	0.257***	0.185***	0.218***	−0.178
	(1.14)	(1.59)	(1.33)	(−0.63)	(−0.54)	(0.15)	(0.78)	(1.01)	(1.10)	(1.35)	(2.20)	(2.93)	(2.98)	(3.47)	(3.49)	(−0.95)
N	578,841	578,841	578,841	575,143	578,841	578,841	578,841	516,687	568,049	548,833	441,787	420,893	473,324	460,387	489,930	343,857
Adjusted R^2	0.148	0.157	0.169	0.169	0.153	0.181	0.150	0.167	0.160	0.183	0.160	0.161	0.161	0.175	0.192	0.361

Table 9: Portfolio-level Fama-MacBeth Regressions

This table reports the results of the Fama-MacBeth two-pass regressions of bond portfolio excess returns on the GDA5 factors. MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. In column (1), we use 5×5 portfolios sorted independently on bond size and maturity. In column (2), we use portfolios aggregated at the Fama-French 30 industry level. In column (3), we use 5×5 portfolios sorted independently on bond size and rating. In column (4), we use 25 portfolios sorted on credit spread. In column (5), we use 5×5 portfolios sorted independently on bond rating and maturity. In column (6), we use 3×3×3 portfolios sorted independently on size, rating, and maturity. In column (7), we use the 32 portfolios constructed by Dickerson, Mueller, and Robotti (2023). In column (8), we use the 35 portfolios constructed by Elkamhi, Jo, and Nozawa (2024) where we exclude the 5 portfolios sorted on downside risk. Factor betas are estimated using lagged rolling windows of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	5 × 5 Size/Maturity	30 FF Industry	5 × 5 Size/Rating	25 Credit Spread	5 × 5 Rating/Maturity	3 × 3 × 3 Size/Rating/Maturity	32 portfolios by Dickerson, Mueller, and Robotti (2023)	35 portfolios by Elkamhi, Jo, and Nozawa (2024)
β_{MKT}	0.408***	0.074	0.120	0.184	0.470***	0.361***	0.297**	0.507***
	(2.64)	(0.40)	(0.90)	(1.14)	(3.08)	(2.94)	(2.10)	(2.75)
β_{DS}	−27.380***	2.068	0.442	0.150	−28.815**	−16.961*	−11.934	−0.673
	(−3.40)	(0.18)	(0.03)	(0.01)	(−2.03)	(−1.83)	(−1.48)	(−0.07)
β_{MKTDS}	0.281**	0.069	0.047	0.106	0.275*	0.197*	0.165	0.057
	(2.13)	(0.44)	(0.31)	(0.68)	(1.73)	(1.80)	(1.65)	(0.41)
β_{VOL}	−0.001	0.005	0.018	0.007	−0.046	−0.004	0.009	−0.019
	(−0.04)	(0.16)	(0.43)	(0.15)	(−1.09)	(−0.10)	(0.20)	(−0.60)
β_{VOLDS}	−0.047*	−0.006	−0.005	−0.013	−0.082**	−0.037	−0.002	−0.029
	(−1.89)	(−0.22)	(−0.14)	(−0.31)	(−2.00)	(−1.11)	(−0.04)	(−0.96)
Constant	0.049	0.361***	0.339***	0.267***	−0.017	0.099	0.156***	−0.003
	(0.55)	(2.83)	(3.43)	(2.86)	(−0.17)	(1.20)	(2.81)	(−0.03)
N	4,950	5,924	4,950	4,925	4,950	5,346	6,304	6,090
Adjusted R^2	0.673	0.412	0.693	0.815	0.819	0.759	0.735	0.796

Table 10: Model Comparison Tests versus the Bond CAPM

This table reports the results of model comparisons of GDA5, BBW4, STK5, BND5, HKM, DEFTERM, CAPM, HKMSF, MACRO, LIQPS, LIQAM, VOLPS, VOLAM, and HKMNT models against the bond CAPM using different sets of test portfolios. In column (1), we use 5×5 portfolios sorted independently on bond size and maturity. In column (2), we use portfolios aggregated at the Fama-French 30 industry level. In column (3), we use 5×5 portfolios sorted independently on bond size and rating. In column (4), we use 25 portfolios sorted on credit spread. In column (5), we use 5×5 portfolios sorted independently on bond rating and maturity. In column (6), we use 3×3×3 portfolios sorted independently on size, rating, and maturity. In column (7), we use the 32 portfolios constructed by Dickerson, Mueller, and Robotti (2023). In column (8), we use the 35 portfolios constructed by Elkamhi, Jo, and Nozawa (2024) where we exclude the 5 portfolios sorted on downside risk. The test statistic is the difference of GLS R^2 between each model and the bond CAPM based on cross-sectional regressions. The p-values in parentheses are calculated following Kan, Robotti, and Shanken (2013) under potential model misspecification. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) 25 Size/Maturity	(2) 30 FF Industry	(3) 25 Size/Rating	(4) 25 Credit Spread	(5) 25 Rating/Maturity	(6) 27 Size/Rating/Maturity	(7) 32 Dickerson et al.	(8) 35 Elkamhi et al.
GDA5	0.152	0.175*	0.351**	0.051	0.200**	0.086	0.236***	0.102**
	(0.514)	(0.062)	(0.049)	(0.828)	(0.011)	(0.431)	(0.008)	(0.016)
BBW4	0.078	0.039	0.081	0.032	0.111	0.033	0.015	0.018
	(0.449)	(0.768)	(0.129)	(0.901)	(0.176)	(0.601)	(0.818)	(0.626)
STK5	-0.118	0.091	0.321**	0.091	0.200	-0.064	0.218	0.144
	(0.559)	(0.468)	(0.016)	(0.665)	(0.357)	(0.652)	(0.186)	(0.422)
BND5	0.116	0.025	0.050	0.207	0.155**	0.002	0.093	0.072
	(0.782)	(0.957)	(0.736)	(0.443)	(0.026)	(0.998)	(0.315)	(0.386)
HKM	-0.154	0.008	0.051	-0.161	-0.190	-0.141	-0.007	-0.044
	(0.311)	(0.919)	(0.571)	(0.244)	(0.122)	(0.200)	(0.918)	(0.451)
DEFTERM	-0.018	-0.035	0.033	-0.086	-0.129	-0.039	-0.082	-0.067
	(0.842)	(0.589)	(0.640)	(0.463)	(0.250)	(0.563)	(0.130)	(0.241)
CAPM	-0.156	0.007	0.036	-0.173	-0.194	-0.147	-0.007	-0.060
	(0.298)	(0.933)	(0.617)	(0.228)	(0.114)	(0.161)	(0.910)	(0.304)
HKMSF	-0.164	-0.006	0.051	-0.206	-0.190	-0.141	-0.026	-0.085
	(0.320)	(0.937)	(0.571)	(0.186)	(0.122)	(0.202)	(0.719)	(0.237)
MACRO	0.019	0.011	0.000	0.045	0.003	0.052	0.032	0.022
	(0.671)	(0.640)	(0.944)	(0.466)	(0.844)	(0.239)	(0.260)	(0.301)
LIQPS	0.152	0.078	0.089	0.268	0.109	0.057	0.213	0.117
	(0.527)	(0.630)	(0.422)	(0.281)	(0.535)	(0.641)	(0.225)	(0.374)
LIQAM	0.114	0.150	0.170	0.162	0.109	0.041	0.272	0.128
	(0.574)	(0.491)	(0.200)	(0.501)	(0.537)	(0.692)	(0.170)	(0.353)
VOLPS	0.176	0.121	0.096	0.274	0.111	0.156	0.216	0.117
	(0.487)	(0.561)	(0.443)	(0.256)	(0.542)	(0.299)	(0.239)	(0.377)
VOLAM	0.116	0.203	0.198	0.186	0.110	0.092	0.282	0.128
	(0.568)	(0.417)	(0.214)	(0.483)	(0.543)	(0.407)	(0.172)	(0.342)
HKMNT	-0.154	0.008	0.037	-0.155	-0.189	-0.143	-0.002	0.003
	(0.299)	(0.924)	(0.613)	(0.327)	(0.130)	(0.188)	(0.975)	(0.972)

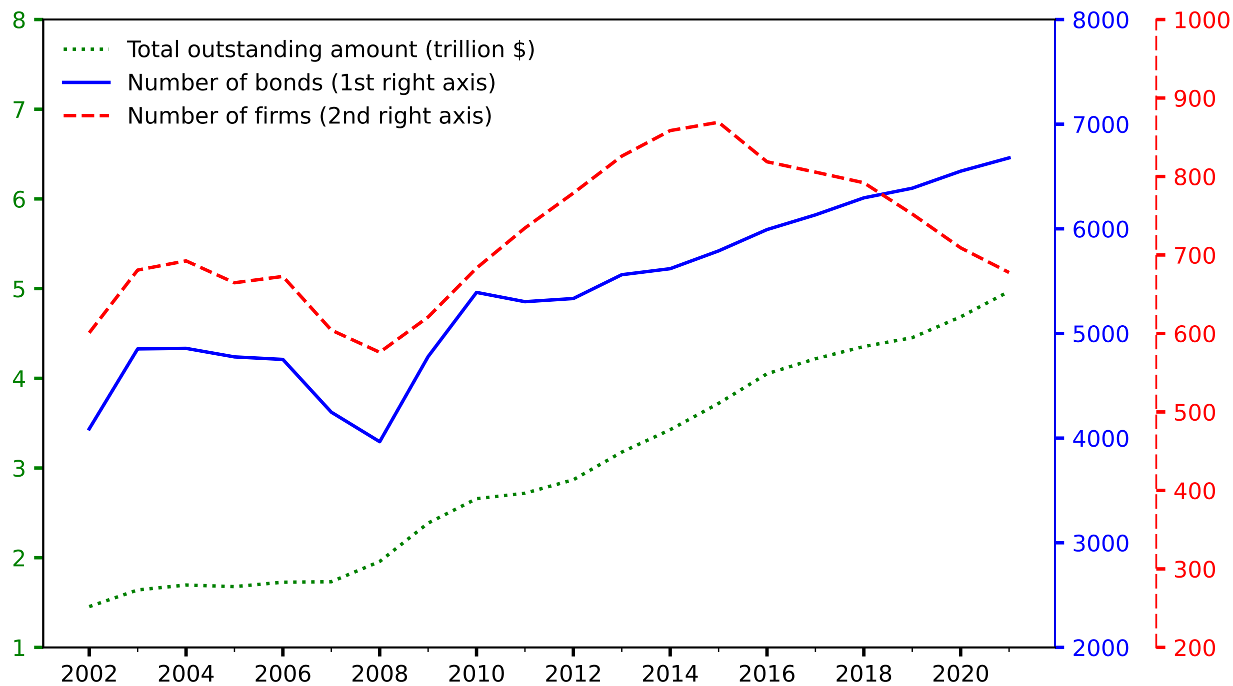

Figure 1: Number of Bonds, Number of Firms and Total Amount Outstanding

This figure plots the number of bonds (blue solid line), number of firms (red dashed line), and the total amount outstanding in $trillion (green dotted line). The sample period is from 2002-2021. Specifically, we first calculate the number of bonds, number of firms, and the total outstanding amount for each month. From the monthly statistics, we then compute yearly averages that are reported in the graph. Source: Trade Reporting and Compliance Engine (TRACE) Enhance data and Mergent Fixed Income Securities Database (FISD).

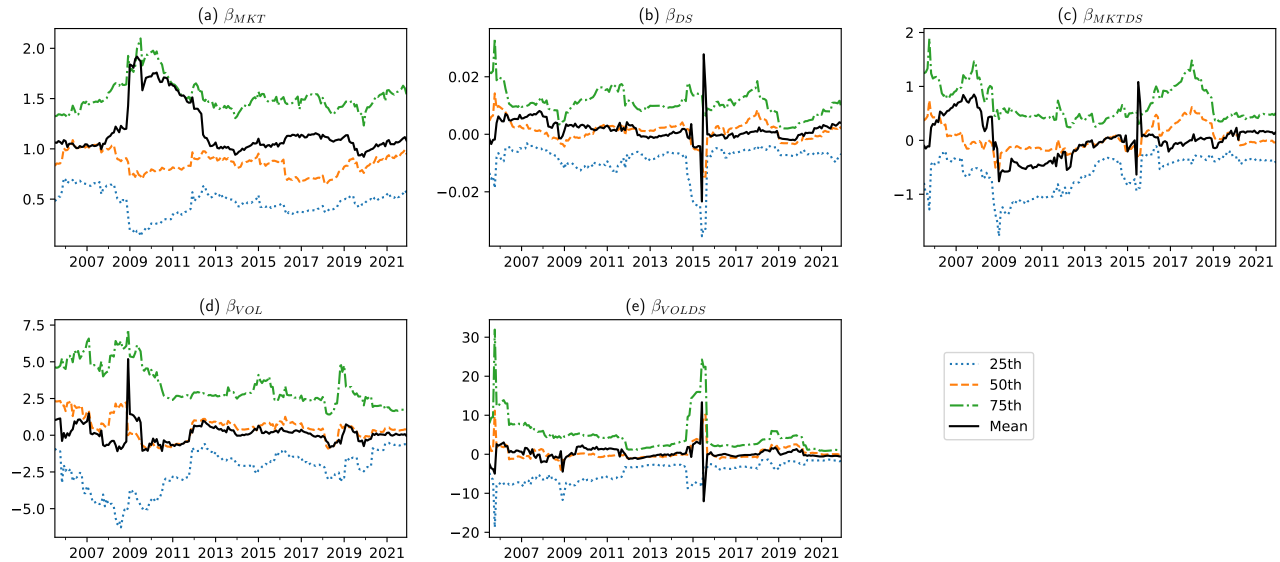

Figure 2: Time-Series Distribution of Estimated GDA5 Factor Betas

This figure plots the distribution of the GDA5 factor betas estimated using rolling windows of 36 months. MKT is the bond market factor, i.e. the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. VOL is the volatility factor calculated from the VIX index. DS is the downside factor, and $MKTDS$ ($VOLDS$) is the market (volatility) downside factor. We plot the cross-sectional mean (solid black line), cross-sectional 25th percentile (blue dotted line), cross-sectional 50th percentile (yellow dashed line), and the cross-sectional 75th percentile (green dash-dotted line) for all five factor betas. The sample period spans from July 2005 to December 2021.

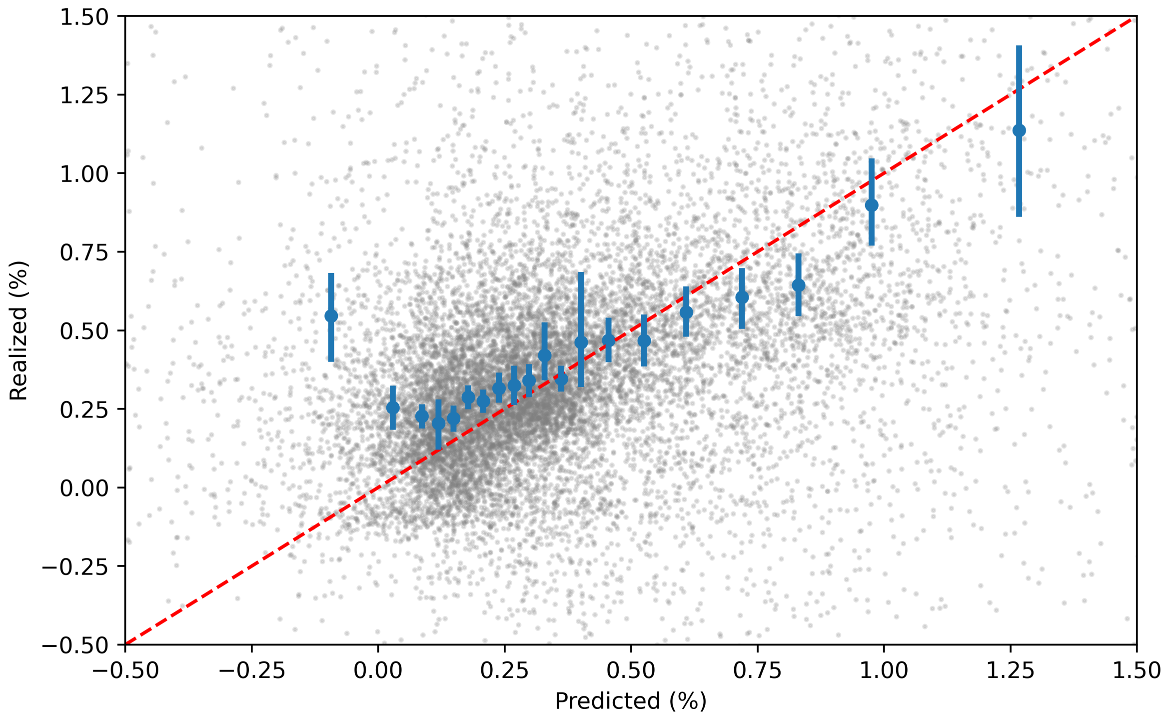

Figure 3: Realized vs. Predicted Excess Returns at the Individual Bond Level

This figure plots the realized mean excess returns against the predicted expected excess returns ($\mathbb{E}[\lambda_F^\top \beta_{iF}]$) from the GDA5 factor model estimated using excess returns measured at the individual bond level and where the prices of risk (λ_F) are estimated from Fama-MacBeth regression without a constant. Each grey dot represents the realized and predicted mean excess return of a bond. For the ease of visualization, we only show the graph for monthly excess returns between -0.50% and 1.5%. We also cut the x-axis (predicted return) into 20 bins with equal numbers of observations and estimate the average realized return in each bin (blue dots), as well as their bootstrapped standard errors (blue error bars) for each bin. The red dashed line indicates the 45° line.

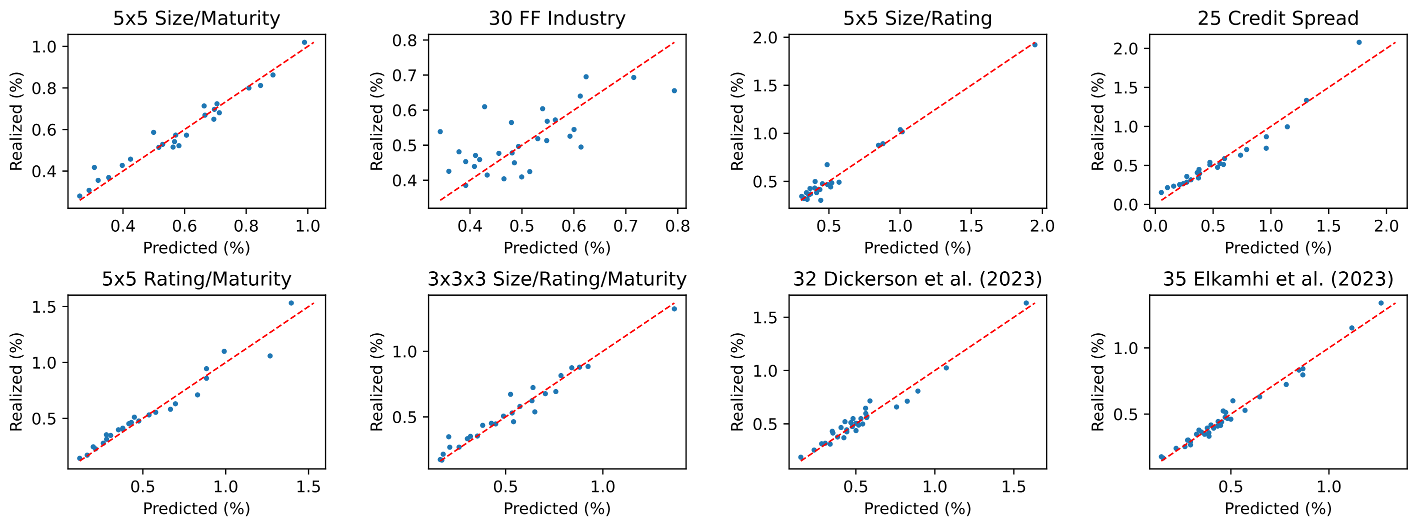

Figure 4: Realized vs. Predicted Returns at the Portfolio Level with Unconditional Betas

This figure plots the realized mean excess returns versus the predicted expected excess returns ($\mathbb{E}[\lambda_F^\top \beta_{iF}]$) from the GDA5 factor model for different sets of test portfolios where the betas are estimated unconditionally over the whole sample period and the prices of risk (λ_F) are estimated from Fama-MacBeth regression without a constant. The red dashed lines indicate the 45° line.

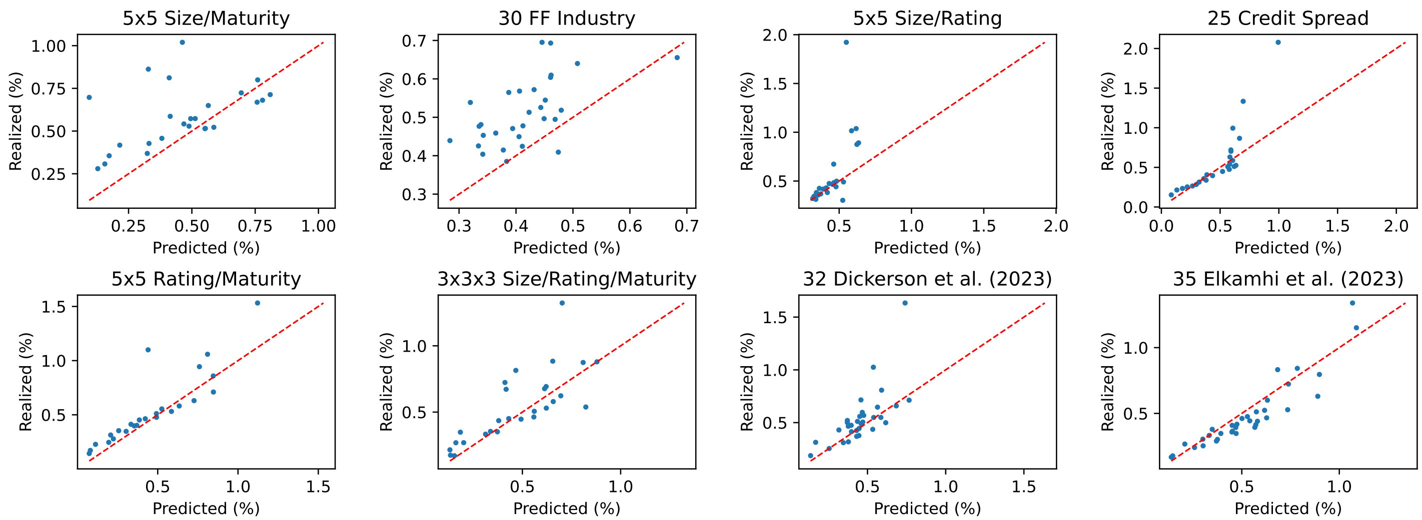

Figure 5: Realized vs. Predicted Returns at the Portfolio Level with Rolling-Window Betas

This figure plots the realized mean excess returns versus the predicted expected excess returns ($\mathbb{E}[\lambda_F^\top \beta_{iF}]$) from the GDA5 factor model for different sets of portfolios where the betas are estimated using 36-month rolling windows and the prices of risk (λ_F) are estimated from Fama-MacBeth regression without a constant. The red dashed lines indicate the 45° line.

Appendix

Downside Risk and the Cross-section of Corporate Bond Returns

In the appendix, we provide details on the construction of the corporate bond data (Appendix A), examine alternative methods to construct the GDA5 factors (Appendix B), and discuss additional robustness tests (Appendix C).

A Constructing Monthly Corporate Bond Returns

We follow Dickerson, Mueller, and Robotti (2023) to construct the cross-section corporate bond returns. We deviate in some instances that we explicitly motivate and further clean the bond transactions data to identify and remove potential erroneous data. All of the text in `code font` refers to SAS code. All results are generated using SAS software version 9.4 TS Level 1M5 and Python 3.10.13[1].

A.1 Filters for the corporate bond transactions data (enhanced TRACE)

We start with the Enhanced TRACE database and use the filters of Dickerson, Mueller, and Robotti (2023) with two major differences: (1) we account for the change in TRACE data fields before and after February 6, 2012;[2] (2) we use a different filter for days to settlement.

More specifically, we first remove canceled transactions and adjust corrected and reversed transactions following Dick-Nielsen (2009) and Dick-Nielsen (2014).[3] Then, for common data fields in both pre-2/6/12 and post-2/6/12 files, we apply the following filters:

1. Remove when-issued trades using `wis_fl^="Y"`;
2. Keep trades with par volume greater than or equal to $10,000 using `entrd_vol_qt>=10000`;
3. Keep trades with reported price between 5 and 1,000 (quoted as percentage points of face value) using `5<rptd_pr<1000`;
4. Remove trades with special trade conditions using `spcl_trd_fl^="Y"`.[4]

Then, we further apply the following filters using different data fields in the two files:

5. Remove equity-linked notes: Pre-2/6/12 file, we require `scrty_type_cd^="E"`; post-2/6/12 file, we require `sub_prdct^="ELN"`.

[1]We mainly use the following Python packages: NumPy 1.23.5, Pandas 1.5.2, and QuantLib 1.29.

[2]On February 6, 2012, TRACE migrated to a new technological platform. This slightly changed the lists of data fields between the pre-2/6/12 file and the post-2/6/12 file, but WRDS directly concatenates the two files including all data fields. Some data fields are available in both files, while some are only available in one file with missing values in the other.

[3]We use the SAS code available from WRDS: https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/wrds-bond-return/cleaning-trace-data/wrds-clean-trace-enhanced-file.

[4]This filter is not used by Dickerson, Mueller, and Robotti (2023), but we think this filter is necessary based on the data manual, which states that "this field indicates the existence of a special trade condition (as defined in FINRA Rule 6730(d)(4)(A)) that impacted the execution price", where FINRA Rule 6730(d)(4)(A) states "if a transaction is not executed at a price that reflects the current market price, select the modifier, 'special price' ".

6. Remove locked-in trades: Pre-2/6/12 file, there is no relevant data field; post-2/6/12 file, we require `lckd_in_ind^="Y"`.

7. Require regular trade with less than 3 days to settlement: pre-2/6/12 file, keep regular trades by requiring `sale_cndtn_cd="@"` and `missing(sale_cndtn2_cd)`. There is no extra information about days to settlement in this file; post-2/6/12 file: keep regular trades by requiring `trd_mod_3 not in ("T","Z","U")` and `trd_mod_4^="W"`.[5] Then, we use CRSP business days from `crsp.dsiy` to calculate days to settlement from `trd_exctn_dt` and `stlmnt_dt`. If `trd_exctn_dt` falls on a non-CRSP business day, we assume that the transaction happens on the next CRSP business day following SEC rules. Then, we only keep observations that, based on these calculcations, have days to settlement less than or equal to 3 business days.

The last filter on days to settlement needs further explanation. Bai, Bali, and Wen (2019) remove transactions with a more than two-day settlement. Dickerson, Mueller, and Robotti (2023) follow the same approach and show that they filter based on `days_to_sttl_ct`. However, this choice may introduce a bias since the SEC adopts T+2 in 2017. Before 2017, transactions used to be settled T+3.[6] Brokers were required to comply with the new rule starting from September 5, 2017.[7] In addition, the data field `days_to_sttl_ct`, which only exists in the pre-2/6/12 file, only represents days to settlement when `sale_cndtn_cd="R"` (Sellers Option Settlement); for other cases, the data field is equal to `"000"` which does not necessarily mean T+0 settlement.[8] In the post-2/6/12, however, there is a new data field `stlmnt_dt` representing the actual settlement date, from which we can calculate the actual days to settlement and apply the filter accordingly. As a result, due to the absence of information on the exact number of days to settlement in the pre-2/6/12 file and the transition from T+3 to T+2 in 2017 during our sample period, we require transactions to be settled in no more than 3 business days only in the post-2/6/12 file.

A.2 Filters for corporate bond characteristics (Mergent FISD)

We retrieve the bond issue sample from Mergent FISD and largely follow the filters from Dickerson, Mueller, and Robotti (2023). We explicitly motivate any deviation. Specifically, we apply the following filters:

1. Keep bonds with issuers in the U.S. using `COUNTRY_DOMICILE="USA"`;
2. Keep bonds traded in US dollar using `FOREIGN_CURRENCY="N"`;
3. Remove convertible bonds using `CONVERTIBLE="N"`;
4. Remove asset backed bonds using `ASSET_BACKED="N"`;
5. Remove bonds traded under Rule 144A using `RULE_144A="N"`;
6. Remove bonds issued via private placements using `PRIVATE_PLACEMENT="N"`;

[5] These filters parallel those based on `sale_cndtn_cd` and `sale_cndtn2_cd`, but the latter two are not available in the post-2/6/12 file. Specifically, by requiring regular trades in the pre-2/6/12, we effectively removes trades that are reported late, with weighted average price, cash sale, next-day settlement, or sellers option settlement. Due to the lack of information on the others in the post-2/6/12 file, we only impose filter based on the first two conditions using `trd_mod_3` and `trd_mod_4`.

[6] See https://www.sec.gov/about/reports-publications/investorpubstplus3htm.

[7] For the press release from SEC, see https://www.sec.gov/news/press-release/2017-68-0. In addition, we use the new data field `stlmnt_dt` available in the post-2/6/12 file to verify this. We find that before September 5, 2017, over 90% of daily transactions are settled T+3 while after that over 90% of daily transactions are settled T+2.

[8] Dickerson, Mueller, and Robotti (2023) require `days_to_sttl_ct` to be one of '001', '002', '000', or 'None'. This only removes transactions with above two-day settlement for transactions with sellers' option settlement before February 6, 2012.

7. Use BOND_TYPE to remove bonds such as equity-linked, agency-backed, U.S. Government, or mortgage-backed bonds. Specifically, we only keep bonds with BOND_TYPE equal to one of the following values: "CMTZ" (US Corporate MTN Zero), "CDEB" (U.S. Corporate Debentures), "RNT" (Retail Note), "CMTN" (U.S. Corporate MTN), "USBN" (U.S. Corporate Bank Note), "PS" (Preferred Security), "UCID" (U.S. Corporate Insured Debenture), "TPCS" (Trust Preferred Capital Security), "CPIK" (U.S. Corporate PIK Bond), or "CZ" (U.S. Corporate Zero), where definitions of each value are available from the Mergent FISD database manual;[9]

8. Remove bonds with missing values for DATED_DATE, INTEREST_FREQUENCY, DAY_COUNT_BASIS, OFFERING_DATE, or MATURITY;

9. Keep zero-coupon bonds or fixed-rate bonds. Sometimes, there is an inconsistency among different data fields. For example, some fixed-rate bonds identified by COUPON_TYPE="F" have zero coupon rate and some zero-coupon bonds identified by COUPON_TYPE="Z" have semi-annual interest frequency (INTEREST_FREQUENCY="2"). As a result, we adopt a conservative approach and only keep bonds satisfying either of the two following conditions: (1) Zero-coupon bonds: identified by COUPON_TYPE="Z" and INTEREST_FREQUENCY="0"; (2) Fixed-rate bonds: identified by COUPON_TYPE="F", coupon>0, not missing(coupon), and INTEREST_FREQUENCY in ("1","2","4","12","99"). Values of INTEREST_FREQUENCY indicate the following payment frequencies: "1" for annually, "2" for semi-annually, "4" for quarterly, "12" for monthly, and "99" for payment at maturity. This is a slightly stricter filter than Dickerson, Mueller, and Robotti (2023);

10. We further remove equity-linked notes by removing bonds if ISSUE_NAME contains "LINK". We manually check these bonds and find that all of them are linked notes such as index-linked, equity-linked, currency-linked, and swap rate-linked notes. This filter is not used by Dickerson, Mueller, and Robotti (2023).

We start with the Mergent FISD bond issue sample of 561,184 bonds. After applying the above filters, we end up with 75,601 bonds. 50,533 of them are in the filtered TRACE data.

A.3 Constructing the daily bond price series

Dickerson, Mueller, and Robotti (2023) construct the daily bond price series by directly calculating the volume-weighted average price among all transactions for each bond on each day. We follow that approach and further clean the price series to identify and remove potential erroneous data using the following steps:

1. We start from the filtered enhanced TRACE transaction data with valid bond information in the filtered Mergent FISD data set (obs: 110,720,031);

2. Then, we aggregate transaction-level data at the bond-timestamp level by calculating the volume-weighted average price (obs: 88,194,095) and the total volume. The timestamp is identified by trd_exctn_dt and trd_exctn_tm;

3. At the same time, we calculate the standard deviation of all prices of the same bond traded at the same timestamp. Then, we obtain the ratio of the standard deviation to the weighted average price. We require that the ratio be no more than 10% since we do not expect that transactions happening at the same time for the same bond should have such large deviation in their prices. This filter slightly reduces the sample size from 88,194,095 to 88,193,294 observations;

4. Then, we apply the Rossi (2014) filter on the timestamp-level bond prices which effectively removes observations with large price reversal or large price deviation among adjacent transactions (within 30 days). This reduces the sample size from 88,193,294 to 87,598,556 observations;

[9] This requirement is identical to Dickerson, Mueller, and Robotti (2023), though instead of keeping these bonds, they remove bonds with BOND_TYPE having other values than the above ones.

5. Finally, for each bond and each day, we calculate the daily price as the volume-weighted average price for all timestamps with available price and volume data (obs: 19,397,104).

Then, we use the QuantLib 1.29 library, which takes into account information such as the day count basis and the interest frequency to calculate the accrued interest and full price for each bond on each day.

A.4 Constructing the monthly bond return series

We closely follow Dickerson, Mueller, and Robotti (2023) in the construction of monthly bond returns. For each bond and each month t, we first check if there are observations in the last 5 trading days of the month. If there is a unique one, we choose its price P_t as the bond price at the end of month t; if there are multiple observations, we choose the one that is closest to the last day of the month; if there is no observation, the bond return in month t is set as missing. Trading days are identified from CRSP (`crsp.dsiy`).

Second, we follow the same method to determine the bond price at the end of month $t-1$, i.e. P_{t-1}. If there is no observation in the last 5 trading days of month $t-1$, we check if there are observations in the first 5 trading days of month t. If there is a unique observation, its price is chosen to be P_{t-1}; if there are multiple observations, the one closest to the first day of month t is chosen; otherwise, the bond return in month t is set as missing. Finally, if both P_t and P_{t-1} are available, the bond return in month t is defined as:

$$R_t = \frac{(P_t + AI_t) + C_t - (P_{t-1} + AI_{t-1})}{P_{t-1} + AI_{t-1}}, \tag{A.1}$$

where AI_t is the accrued interest from the last coupon payment day, i.e. $P_t + AI_t$ is the full (or dirty) price of the bond, and C_t is the coupon payment in month t. As in Dickerson, Mueller, and Robotti (2023), we do not winsorize bond returns.

Finally, we remove return observations if the bond has less than 1 year to maturity as in Dickerson, Mueller, and Robotti (2023) and van Binsbergen, Nozawa, and Schwert (2024).

B Alternative Methods to Construct the GDA5 Factors

We check the robustness of the GDA5 model in explaining the cross-sectional variation in corporate bond returns to different methods of constructing the GDA5 factors.

B.1 Volatility factor estimated from conditional EGARCH variance

For our baseline results, we use the Cboe VIX volatility index to construct the volatility factor. As a robustness check, we estimate as an alternative volatility factor the following EGARCH model using daily market factors over the whole sample period:

$$r_{W,t} = \mu + \sigma_{W,t}\varepsilon_t, \quad \varepsilon_t \sim \text{i.i.d. } \mathcal{N}(0,1), \tag{A.2}$$

$$\ln(\sigma^2_{W,t}) = w + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - \sqrt{2/\pi}) + \delta \ln(\sigma^2_{W,t-1}), \tag{A.3}$$

where $r_{W,t}$ is the MKT factor. We obtain the fitted daily variance and take the sum as the monthly variance. Then, we use its monthly change as the proxy for our volatility factor. Column (2) of Table A.3 reports the results of the Fama-MacBeth regression of the GDA5 factor model when VOL is constructed from the full-sample EGARCH model, whereas column (1) repeats our baseline results. The MKT and $VOLDS$

factors are significant at a 5% significance level, while $MKTDS$ and VOL factors are significant at a 10% significance level. Due to the relatively low volatility of the bond market return, the prices of risk for VOL and $VOLDS$ are smaller than those in our baseline results where VOL is constructed from the VIX index. In addition, the intercept remains statistically insignificant.

B.2 Volatility factor constructed from macroeconomic uncertainty

Bali, Subrahmanyam, and Wen (2021b) show that economic uncertainty, proxied by the Jurado, Ludvigson, and Ng (2015) macroeconomic uncertainty index is priced in the cross-section of corporate bond returns. As a robustness check, we, therefore, use the macroeconomic uncertainty index to proxy for the GDA5 volatility factor. As shown by Bali, Subrahmanyam, and Wen (2021b), the macroeconomic uncertainty index aligns well with the VIX index, so we consider the index as a measure of volatility and estimate the associated variance as its squared value. Then, the volatility factor is defined as the monthly change in the estimated variance.[10]

Column (3) of Table A.3 reports the Fama-MacBeth regression of the GDA5 model using the VOL factor estimated from the macroeconomic uncertainty index. Four of the five GDA5 factors are significant at a 5% or higher significance level. In particular, DS becomes insignificant while VOL becomes significant. Since the macroeconomic uncertainty index is constructed from a large panel of economic and financial data, the additional information incorporated in the index, in excess of the VIX index, is useful in explaining the cross-section of corporate bond returns which subsumes the explanatory power of the pure downside factor.

B.3 Different values of model parameters

For our baseline results, we choose $p = 25\%$ to have a probability of downside states equal to 25%. Table A.4 reports results using different values of $p \in \{10\%,15\%,20\%,25\%\}$ to construct the GDA5 downside factors. The corresponding values of parameter b are also shown at the bottom of the table. In column (1), when the probability of downside states is too low, we lose many observations since there may not be enough downside states to estimate GDA5 factor betas accurately for some periods. While we maintain the robustness of our results, the statistically weaker performance of the GDA5 model is due to a a significant smaller sample size of 269,560 observations.

In column (2), at $p = 15\%$, $MKTDS$ and $VOLDS$ are significant at a 5% significance level, while DS is significant at a 10% significance level. All of the downside factors are significant at a 5% significance level or higher when $p = 20\%$ in column (3).

The calibration of the downside states in our baseline results also depends on $a = 1$ to give equal importance to the market and volatility factor in determining the downside states. Table A.5 reports results when we use different values of parameter $a \in \{0.50,0.75,1.00,1.25\}$ to construct the GDA5 factors. For all values of a, we find that four of five GDA5 factors are significant, with the exception of VOL. These results are similar to our benchmark results both in statistical significance and in economic magnitude.

C Additional Robustness Checks

We consider alternative window lengths to estimate the factor betas, alternative lag lengths to correct the standard errors, and different ways to compare the GDA5 factor model to models that that also include a market factor.

[10] Bali, Subrahmanyam, and Wen (2021b) uses the monthly change of the uncertainty index since the index itself is serially correlated. To align more closely with the theoretical framework of Farago and Tédongap (2018), we use the monthly change of variance.

C.1 Alternative window lengths to estimate factor betas

For our baseline results, we align with the literature and estimate the factor betas using rolling window lengths of 36 months (Dickerson, Mueller, and Robotti, 2023). To show that the performance of the GDA5 model is robust to different window lengths, we consider alternative rolling window lengths of 48, 60, and 72 months, respectively. Using each of these rolling windows, we estimate our factor betas using Eq. (8). Table A.6 reports these results. As the size of the rolling window increases, we lose observations at the beginning of the sample period but obtain more observations for the later periods since more betas can be estimated. Thus, the number of observations changes with different lengths of the rolling window. Our main results are robust to the length of the rolling window. Across all different specifications, four of five GDA5 factors are significant at a 5% or higher significance level, with the exception of DS which is significant at a 10% significance level when we use a 72-month rolling window. The average adjusted R^2s are similar across specifications. These results are qualitatively and quantitatively similar to our benchmark results.

C.2 Alternative lags for the Newey-West standard error correction

We estimate standard errors following Newey and West (1987) to correct for serial correlation in the error terms. The Newey-West estimator requires a choice on the number of lags. In our main specification, we use 4 lags for the estimation based on the rule of thumb formula $L \approx T^{1/4}$ (see, e.g., page 521 of Greene (2018)). To show that our results do not rely on this choice, we repeat our baseline estimation with 2, 3, 5, and 6 lags for the Newey-West estimator. Table A.7 reports these results and we find that our main results are robust to different number of lags.

C.3 Controlling for bond market betas from BBW4 and BND5

Both the BBW4 and BND5 models contain the same bond market factor MKT as the GDA5 model. In our main specification of the Fama-MacBeth regression, we include all of the GDA5 factor betas, as well as all of BBW4's (BND5's) factor betas, except their bond market betas. We conduct additional tests to show that the pricing power of the GDA5 model is robust to including the BBW4 or BND5 market factor betas, respectively.

We report in column (1) of Table A.8 the baseline estimation from column (2) of Table 5. In column (2), we include all of the four factor betas of the BBW4 model, as well as all GDA5 factor betas, except the GDA5 MKT beta. BBW4's $MKTB$ factor beta is significant at a 1% significance level. In addition, both DRF and LRF are significant at a 5% significance level. Nonetheless, all of the remaining four GDA5 factor betas remain significant.

In column (3), we further include all of the GDA5 factor betas (including MKT) and all of the BBW4 factor betas. All of the GDA5 factors remain significant at a 5% or higher significance level, while all of the BBW4 factors are statistically insignificant. Note that the time-series average of the cross-sectional correlation coefficient between GDA5's MKT and BBW4's $MKTB$ beta is 9% (it ranges from -50% to 70%), so there is no severe multicollinearity issue.

In columns (4) and (5), we repeat the estimation of columns (1) and (2), with BBW4 betas estimated following the methodology in Bai, Bali, and Wen (2019), that is, the $MKTB$ beta is estimated in a univariate regression while the other four factor betas are estimated by controlling only for $MKTB$. In both specifications, all of the GDA5 factors remain statistically significant.

In columns (6)-(8), we repeat the estimation of columns (1)-(3) controlling for the BND5 factor betas. Recall that we have a reduction in the sample size since constructing $LIQB$ in the BND5 model requires a data lag of 60 months following Lin, Wang, and Wu (2011). Across these specifications, all of the GDA5 factor betas are still significant at a 10% or higher significance level. The BND5 factors are insignificant except for the $MKTB$ factor, which is significant in column (7), and the $TERM$ factor, which is marginally significant in column (7) as well.

Table A.1: Variable Definitions

Main Variables	Definitions
	Panel A: Bond-level variables
Bond excess return	Bond monthly return minus 1-month Treasury rate. Bond return is constructed following Dickerson, Mueller, and Robotti (2023) using bond transaction data from TRACE and bond information from Mergent FISD. The 1-month Treasury rate is from Kenneth French's website.[11]
Duration-adjusted return	Bond monthly return minus duration-matched Treasury return following van Binsbergen, Nozawa, and Schwert (2024). Data on Treasury yield curve is from Gürkaynak, Brian Sack, and Wright (2007).
Rating	The average of S&P's and Moody's credit rating for corporate bonds from Mergent FISD, coded from AAA=1 to D=22 for S&P's and Aaa=1 to C=21 for Moody's. If either one is missing, we use the other one instead.
Maturity	Number of years until the maturity date from Mergent FISD.
Bond size	The amount outstanding of bond in million USD from Mergent FISD.
BPW illiq	We first calculate monthly bond illiquidity following Bao, Pan, and Wang (2011), defined as $-Cov_t(\Delta p_{i,t,d}, \Delta p_{i,t,d+1})$ where $\Delta p_{i,t,d} = \ln(P_{i,t,d}/P_{i,t,d-1})$ is the log return of bond i on day d of month t. The covariance is calculated using daily bond return in month t, requiring a maximum of 7 days between two observations to recognize a daily log return and a minimum of 10 observations for each month for the calculation. Then, to reduce the impact of missing values, for each bond and each month, we supplement missing values of illiquidity by the average of monthly illiquidity in the past 12 months.
DFL illiq	The λ measure proposed by Dick-Nielsen, Feldhütter, and Lando (2012) which is the sum of standardized four liquidity measures: the Amihud measure, imputed round-trip cost (IRC), Amihud risk, and IRC risk. Then, to reduce the impact of missing values, for each bond and each month, we supplement missing values of illiquidity by the average of monthly illiquidity in the past 12 months.
Coupon	Coupon rate in percentage points from Mergent FISD.
Bond age	Number of years since the bond's offering date from Mergent FISD.
VaR5	The negation of the 5% VaR for each bond in each month using monthly returns in the past 36 months, requiring a minimum of 24 months, following Bai, Bali, and Wen (2019).
Lagged return	Bond return in the previous month.

[11] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Panel B: Firm-level variables	
# Inst.	Number of institutional owners, from Thomson-Reuters 13F data.[12]
% IO	Percentage of equity shares held by institutional owners, from Thomson-Reuters 13F data.
# Analysts	Number of analysts forecasting the issuer's earnings per share, based on data from I/B/E/S.[13]
Forecast Disp.	The standard deviation of most recent quarterly analysts' forecast of earnings per share divided by the absolute mean forecast, based on data from I/B/E/S.
Stock excess return	Monthly stock return of the issuer from CRSP, less the 1-month Treasury rate.
Panel C: GDA5 factors	
MKT	Outstanding amount-weighted average return of all bonds in our sample based on data from TRACE and Mergent FISD, less 1-month Treasury rate from Kenneth French's website.
VOL	Monthly change in market variance following Farago and Tédongap (2018), where (monthly) market variance is defined as $(VIX/100)^2/12$. The VIX index is obtained from Cboe Global Markets.
DS	A binary factor defined as: $$DS_t = \left\{ MKT_t - a\frac{\sigma_{MKT}}{\sigma_{VOL}} VOL_t < b \right\},$$ following Farago and Tédongap (2018). σ_{MKT} is the standard deviation of MKT and σ_{VOL} is the standard deviation of VOL. We set $a = 1$ in our main specification and obtain b such that the probability of downside state ($DS_t = 1$) is $p = 25\%$. The corresponding b is -0.0046.
$MKTDS$	MKT multiplied by DS.
$VOLDS$	VOL multiplied by DS.
Panel D: Alternative traded factors	
$MKTS$	Fama and French (1993) stock market factor from Kenneth French's website.
SMB	Fama and French (1993) SMB factor from Kenneth French's website.

[12] We utilize the SAS code from WRDS to compute # Inst. and % IO: https://wrds-www.wharton.upenn.edu/pages/wrds-research/applications/institutional-ownership-research/institutional-ownership-concentration-and-breadth-ratios/.

[13] We use the SAS code from WRDS to calculate # Analysts and Forecast disp.: https://wrds-www.wharton.upenn.edu/pages/wrds-research/applications/programming-examples-and-other-topics/guide-measuring-investors-opinion-divergence-divop.

HML	Fama and French (1993) HML factor from Kenneth French's website.
UMD	Carhart (1997) momentum factor from Kenneth French's website.
$LIQS$	Pástor and Stambaugh (2003) stock liquidity factor from Lubos Pastor's website.[14]
$MKTB$	Outstanding amount-weighted average return of all bonds in our sample based on data from TRACE and Mergent FISD, less 1-month Treasury rate from Kenneth French's website. Same as MKT in the GDA5 factor model.
DRF	Constructed following Bai, Bali, and Wen (2019): For each bond and in each month, we calculate the 5% VaR as defined above and retrieve credit ratings from Mergent FISD. Then, we form 5×5 portfolios by independently sorting bonds on their 5% VaR and credit ratings, respectively. For each of the 25 portfolios, we calculate its monthly outstanding amount-weighted average return among all bonds in the portfolio. Then, we calculate the average return of the top 5% VaR quintile portfolios across all credit rating quintiles and repeat the calculation for the bottom 5% VaR quintile portfolios. Their difference is defined as the DRF factor.
LRF	Constructed following Bai, Bali, and Wen (2019): For each bond and in each month, we calculate BPW illiquidity as defined above. To stick to Bai, Bali, and Wen (2019), we do not supplement missing values with the past 12-month average. Then, we form 5×5 portfolios by independently sorting bonds on their illiquidity and credit ratings, respectively. For each of the 25 portfolios, we calculate its monthly outstanding amount-weighted average return among all bonds in the portfolio. Then, we calculate the average return of the top illiquidity quintile portfolios across all credit rating quintiles and repeat the calculation for the bottom illiquidity quintile portfolios. Their difference is defined as the LRF factor.
CRF	Constructed following Bai, Bali, and Wen (2019): For the 5×5 5%VaR and ratings portfolios, we calculate the average return of the low rating (high credit risk) quintile portfolios across all 5% VaR quintiles and repeat the calculation for the high rating quintile portfolios. Their difference is defined as CRF_{VaR}. Then, the procedure is repeated for illiquidity and lagged return to obtain CRF_{Illiq} and CRF_{REV}, respectively. Then, their average is defined as the CRF factor.
DEF	The difference between long-term corporate bond return and long-term government bond return, downloaded from Amit Goyal's website.[15]
$TERM$	The difference between long-term government bond return and 1-month Treasury rate, downloaded from Amit Goyal's website.

[14] https://faculty.chicagobooth.edu/lubos-pastor/data
[15] https://sites.google.com/view/agoyal145

$MOMB$	Bond momentum factor constructed following Jostova, Nikolova, Philipov, and Stahel (2013): For each bond in month t, we calculate its cumulative return from month $t-7$ to month $t-2$ and then assign bonds into 5×5 portfolios by independently sorting based on credit rating and cumulative return. Then, we calculate the equal-weighted return of each portfolio. Finally, we calculate the average return of all winner quintile portfolios and that of all loser quintile portfolios. Their difference is defined as the $MOMB$ factor.
$LIQB$	This is the traded Pastor-Stambaugh bond liquidity factor constructed following Bai, Bali, and Wen (2019) and Lin, Wang, and Wu (2011): First, $LIQBPS$ is calculated as described in this table. Then, for each bond and each month, we estimate liquidity beta using data in the past 60 months (requiring at least 15 observations) by regressing bond monthly excess return on $MKTS$, SMB, HML, DEF, $TERM$, and $LIQBPS$ and the estimated coefficient of $LIQBPS$ is the liquidity beta. Then, bonds are allocated into 10 decile portfolios by sorting on their liquidity beta and the average return difference between the top decile and bottom decile is defined as $LIQB$.
$CPTLT$	The value-weighted equity return for the New York Fed's primary dealer sector, downloaded from Zhiguo He's website.[16]
	Panel E: Alternative non-traded factors
ΔUNC	The first difference of 1-month-ahead economic uncertainty index downloaded from Sydney Ludvigson's website.[17]
$LIQBPS$	The Pastor-Stambaugh bond liquidity factor constructed following Lin, Wang, and Wu (2011): For each bond in each month, we estimate the following time-series regression to obtain π: $$r^e_{t+1} = a_0 + a_1 r_t + \pi \cdot sign(r^e_t) Vol_t + \varepsilon_{t+1},$$ using daily bond data in the month. We require at least 10 observations for the estimation. r^e_{t+1} is the bond daily return in excess of bond market return on day $t+1$ and r_t is the daily bond return on day t. $sign(r^e_t)$ is an indicator function that is equal to 1 if r^e_t is positive and -1 otherwise. Vol_t is the dollar volume, i.e. volume in million \$ multiplied by bond full price quoted for \$1 face value. Then, we calculate π_t as the average of estimated π across all bonds in month t and define $\Delta\pi_t = (M_t/M_1)(\pi_t - \pi_{t-1})$ where M_t is the market capitalization, i.e. the sum of outstanding amount in million \$ multiplied by its full price quoted for \$1 face value across all bonds in month t. Finally, we estimate the following time-series regression using monthly data over the sample period: $$\Delta\pi_t = b_0 + b_1 \Delta\pi_{t-1} + a_2(M_{t-1}/M_t)\pi_{t-1} + \varepsilon_t,$$ and the Pastor-Stambaugh bond liquidity factor ($LIQBPS$) is defined as $L_t = 100\hat{\varepsilon}_t$.

[16] https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/
[17] See https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

$LIQBAM$	The Amihud bond liquidity factor constructed following Lin, Wang, and Wu (2011): For each bond in each month, we calculate the Amihud illiquidity measure as: $$ILLIQ_{it} = \frac{1}{N}\sum_{i=1}^{N}\frac{\lvert r_{i,j,t}\rvert}{Vol_{i,j,t}},$$ where $r_{i,j,t}$ ($Vol_{i,j,t}$) is the return (trading volume in million \$) of bond i on day j in month t and N is the number of days with available return and trading volume. Then, the market-wide $ILLIQ_{Mt}$ is defined as the cross-sectional average of $ILLIQ_{it}$ over all bonds in month t, after winsorizing $ILLIQ_{it}$ in each cross section using the 1st and 99th percentiles. Then, let $ILLIQ_{Mt} = (M_t/M_1)(ILLIQ_{Mt} - ILLIQ_{M,t-1})$ where M_t is the same as that in the definition of $LIQBPS$. Then, the following time series regression is estimated as: $$\Delta ILLIQ_{Mt} = \phi_0 + \phi_1 \Delta ILLIQ_{M,t-1} + \phi_2 (M_{t-1}/M_1) ILLIQ_{M,t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2},$$ where we exclude the dummy variables d_1 and d_2 in Lin, Wang, and Wu (2011) since we use TRACE Enhanced data, following Chung, Wang, and Wu (2019). Finally, the Amihud bond liquidity factor is defined as $LIQBAM = -\hat{\varepsilon}_t$.
ΔVIX	The first difference of end-of-month VIX index from Cboe Global Markets.
$CPTL$	The non-traded intermediary capital risk factor from He, Kelly, and Manela (2017), downloaded from Zhiguo He's website.

Table A.2: Principal Component Analysis of Bonds and Stocks

This table reports the explanatory power of each of the first ten principal components (PC) for a sample of bond and stock returns, respectively, as well as the cumulative explanatory power of these principal components. We first keep bonds in our sample with valid monthly returns in over 60% of the sample period. This leaves 557 bonds in the sample. Then, we perform probabilistic principal component analysis. For the stock returns, we retrieve monthly individual stock returns from CRSP and also keep stocks with valid monthly returns in over 60% of the sample period. This leaves 4,641 stocks in the sample. Then, we randomly draw 557 stocks from them and perform probabilistic principal component analysis, which is repeated 100 times. Finally, we report the average of the percentage of variation that is explained by the first ten principal components. The sample period spans from July 2002 to December 2021.

	Corporate Bonds		Stocks	
	Percentage of Variation Explained	Cum. Percentage of Variation Explained	Percentage of Variation Explained	Cum. Percentage of Variation Explained
PC1	34%	34%	21%	21%
PC2	13%	47%	14%	35%
PC3	10%	57%	9%	44%
PC4	8%	65%	7%	51%
PC5	6%	71%	5%	56%
PC6	6%	77%	4%	60%
PC7	5%	81%	3%	63%
PC8	4%	85%	3%	66%
PC9	3%	88%	2%	68%
PC10	3%	91%	2%	70%

Table A.3: Bond-level Fama-MacBeth Regressions: Different Measures of Volatility

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factor model with different measures of volatility to construct the VOL factor. MKT is the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate. In column (1), we show our baseline results as in Table 3 for comparison, where VOL is constructed from the VIX index. In column (2), VOL is the change in variance based on an EGARCH model estimated using MKT. In column (3), we use the macroeconomic uncertainty from Jurado, Ludvigson, and Ng (2015) to construct the VOL factor. DS is the downside factor. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor, i.e. MKT (VOL) multiplied by DS. Factor betas are estimated in rolling windows using data with a lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) VIX	(2) EGARCH	(3) MAC. UNC.
β_{MKT}	0.352**	0.362**	0.406***
	(2.50)	(2.45)	(2.68)
β_{DS}	−13.190**	−11.449	−5.502
	(−2.29)	(−1.55)	(−1.09)
β_{MKTDS}	0.253***	0.147*	0.166***
	(2.96)	(1.91)	(2.81)
β_{VOL}	−0.019	−0.001*	−0.675**
	(−1.11)	(−1.75)	(−2.07)
β_{VOLDS}	−0.034**	−0.002**	−0.667**
	(−2.13)	(−2.37)	(−2.42)
Constant	0.108	0.122	0.073
	(1.14)	(1.24)	(0.54)
N	578,841	577,962	573,798
Adjusted R^2	0.148	0.130	0.143

Table A.4: Bond-level Fama-MacBeth Regressions: Different Downside Probabilities p

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factor model with different values of downside probabilities p. MKT is the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate and the VOL factor is constructed from the VIX index. DS is the downside factor. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor, i.e. MKT (VOL) multiplied by DS. In columns (1)-(4), we calibrate to have a probability of downside states of $p = 10\%$, $p = 15\%$, $p = 20\%$, and $p = 25\%$ respectively, where $p = 25\%$ is our baseline specification. The corresponding values of the downside state parameter b are shown at the bottom of each column. Factor betas are estimated using rolling windows with a lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) p=10%	(2) p=15%	(3) p=20%	(4) p=25%
β_{MKT}	0.472***	0.287**	0.330**	0.352**
	(3.00)	(2.34)	(2.58)	(2.50)
β_{DS}	−10.159*	−6.835*	−9.707**	−13.190**
	(−1.74)	(−1.78)	(−2.02)	(−2.29)
β_{MKTDS}	0.233**	0.150**	0.223***	0.253***
	(2.36)	(2.25)	(3.07)	(2.96)
β_{VOL}	−0.028	−0.015	−0.017	−0.019
	(−0.76)	(−0.86)	(−0.98)	(−1.11)
β_{VOLDS}	−0.050*	−0.028**	−0.031**	−0.034**
	(−1.68)	(−2.13)	(−2.00)	(−2.13)
Constant	0.259*	0.164*	0.132	0.108
	(1.66)	(1.86)	(1.45)	(1.14)
N	269,560	543,880	575,403	578,841
Adjusted R^2	0.166	0.138	0.145	0.148
b	−0.0233	−0.0138	−0.0084	−0.0046

Table A.5: Bond-level Fama-MacBeth Regressions: Different Values of Downside Parameter a

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factor model with different values of the downside state parameter a. MKT is the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate and the VOL factor is constructed from the VIX index. DS is the downside factor. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor, i.e. MKT (VOL) multiplied by DS. In columns (1)-(4), we use $a = 0.50$, $a = 0.75$, $a = 1.00$, and $a = 1.25$, respectively, where $a = 1.00$ is our baseline specification. The corresponding values of the downside state parameter b are shown at the bottom of each column. Factor betas are estimated using rolling windows with a data lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) a=0.50	(2) a=0.75	(3) a=1.00	(4) a=1.25
β_{MKT}	0.337**	0.341**	0.352**	0.351**
	(2.46)	(2.48)	(2.50)	(2.53)
β_{DS}	−13.386**	−13.349**	−13.190**	−12.477**
	(−2.24)	(−2.26)	(−2.29)	(−2.13)
β_{MKTDS}	0.242***	0.254***	0.253***	0.254***
	(2.95)	(3.04)	(2.96)	(2.98)
β_{VOL}	−0.024	−0.022	−0.019	−0.018
	(−1.27)	(−1.18)	(−1.11)	(−1.00)
β_{VOLDS}	−0.037**	−0.034*	−0.034**	−0.033*
	(−2.21)	(−1.97)	(−2.13)	(−1.86)
Constant	0.127	0.121	0.108	0.109
	(1.31)	(1.24)	(1.14)	(1.16)
N	578,162	578,171	578,841	579,042
Adjusted R^2	0.148	0.147	0.148	0.148
b	−0.0043	−0.0041	−0.0046	−0.0050

Table A.6: Bond-level Fama-MacBeth Regressions: Different Beta Estimations Periods

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factor model when we use different window lengths to estimate the betas. MKT is the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate and the VOL factor is constructed from the VIX index. DS is the downside factor. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor, i.e. MKT (VOL) multiplied by DS. In columns (1)-(4), we use 36, 48, 60, and 72 months to estimate the betas, respectively, requiring a minimum of 24 observations, where 36 months is used in our baseline specification. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Refer to Table A.1 for detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) 36 months	(2) 48 months	(3) 60 months	(4) 72 months
β_{MKT}	0.352**	0.372**	0.405**	0.456***
	(2.50)	(2.54)	(2.47)	(2.78)
β_{DS}	−13.190**	−13.406**	−12.037**	−10.963*
	(−2.29)	(−2.44)	(−2.05)	(−1.82)
β_{MKTDS}	0.253***	0.274***	0.266***	0.292***
	(2.96)	(2.95)	(2.81)	(2.97)
β_{VOL}	−0.019	−0.020	−0.010	−0.015
	(−1.11)	(−1.25)	(−0.58)	(−0.75)
β_{VOLDS}	−0.034**	−0.035**	−0.033**	−0.038**
	(−2.13)	(−2.38)	(−2.11)	(−2.04)
Constant	0.108	0.139	0.119	0.108
	(1.14)	(1.45)	(1.17)	(1.02)
N	578,841	594,586	582,202	563,604
Adjusted R^2	0.148	0.135	0.126	0.118

Table A.7: Bond-level Fama-MacBeth Regressions: Different Number of Newey-West Lags

This table reports the results of the Fama-MacBeth two-pass regressions of the GDA5 factor model using different numbers of lags for the Newey-West standard error correction. MKT is the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate and the VOL factor is constructed from the VIX index. DS is the downside factor. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor, i.e. MKT (VOL) multiplied by DS. In columns (1)-(5), we show results using 2, 3, 4, 5, and 6 lags, respectively, to correct standard errors according to Newey and West (1987), where 4 lags are used in our baseline specification. Factor betas are estimated using rolling windows with a data lag of 36 months and requiring a minimum of 24 observations. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1) 2 lags	(2) 3 lags	(3) 4 lags	(4) 5 lags	(5) 6 lags
β_{MKT}	0.352***	0.352**	0.352**	0.352**	0.352**
	(2.62)	(2.56)	(2.50)	(2.38)	(2.33)
β_{DS}	−13.190**	−13.190**	−13.190**	−13.190**	−13.190**
	(−2.21)	(−2.28)	(−2.29)	(−2.25)	(−2.25)
β_{MKTDS}	0.253***	0.253***	0.253***	0.253***	0.253***
	(3.21)	(3.08)	(2.96)	(2.84)	(2.76)
β_{VOL}	−0.019	−0.019	−0.019	−0.019	−0.019
	(−1.16)	(−1.13)	(−1.11)	(−1.09)	(−1.07)
β_{VOLDS}	−0.034**	−0.034**	−0.034**	−0.034**	−0.034**
	(−2.30)	(−2.20)	(−2.13)	(−2.08)	(−2.01)
Constant	0.108	0.108	0.108	0.108	0.108
	(1.21)	(1.14)	(1.14)	(1.11)	(1.12)
N	578,841	578,841	578,841	578,841	578,841
Adjusted R^2	0.148	0.148	0.148	0.148	0.148

Table A.8: Bond-level Fama-MacBeth Regressions: Controlling for Different Bond Market Factors

This table reports additional results of the Fama-MacBeth two-pass regressions of individual bond excess returns on the GDA5 factors when we control for the BBW4 and BND5 betas. In the GDA5 factor model, MKT is the outstanding amount-weighted average return of all bonds in the sample minus the 1-month Treasury rate and VOL is constructed from the VIX index. DS is the downside factor constructed. $MKTDS$ ($VOLDS$) is the market (volatility) downside factor, i.e. MKT (VOL) multiplied by DS. In columns (1)-(3) and columns (6)-(8), all factor betas in the same model are estimated jointly while in columns (4)-(5), we BBW4 factor betas are estimated following Bai, Bali, and Wen (2019): bond market betas are estimated in univariate regressions and DRF, LRF, and CRF betas are estimated individually by controlling only for the bond market factor. Estimation of betas are conducted based on rolling windows with a data lag of 36 months and requiring a minimum of 24 observations. In column (1), we repeat the estimation in Table 5 for GDA5 and BBW4. In column (2), we use the bond market beta from BBW4 in place of that from GDA5. In column (3), we include both GDA5's and BBW4's market betas. In column (4), we include GDA5 betas controlling for BBW4's DRF, LRF, and CRF betas estimated only controlling for the bond market factor. In column (5), we replace GDA5's market beta by BBW4's univariate market beta. In column (6), we repeat the estimation in Table 5 for GDA5 and BND5. In column (7), we use BND5's bond market beta in place of GDA5's. In column (8), we include both GDA5's and BND5's market betas. All prices of risk are in percentage points. Time-series averages of cross-sectional adjusted R^2 and the number of observations (N) are reported at the bottom of each column. Table A.1 provides detailed variable definitions. Standard errors are corrected according to Newey and West (1987) with 4 lags. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% (two-tailed) test levels, respectively. The sample period spans from July 2002 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{MKT}	0.344***		0.216**	0.347***		0.329***		0.247***
	(3.12)		(2.27)	(2.96)		(3.50)		(2.79)
β_{DS}	−15.084***	−9.360***	−12.198***	−14.209***	−9.512***	−11.918***	−7.080***	−10.411***
	(−3.58)	(−3.89)	(−3.25)	(−3.28)	(−3.57)	(−4.40)	(−3.27)	(−4.15)
β_{MKTDS}	0.222***	0.104**	0.173***	0.207***	0.070*	0.211***	0.104***	0.176***
	(2.96)	(2.53)	(3.11)	(2.71)	(1.72)	(4.25)	(3.30)	(4.23)
β_{VOL}	−0.055***	−0.035**	−0.048***	−0.052***	−0.027**	−0.055***	−0.036*	−0.049**
	(−3.97)	(−2.58)	(−2.82)	(−4.15)	(−2.01)	(−2.88)	(−1.92)	(−2.38)
β_{VOLDS}	−0.040***	−0.030***	−0.035***	−0.035***	−0.022***	−0.040**	−0.031*	−0.036**
	(−3.48)	(−3.06)	(−3.15)	(−3.75)	(−2.87)	(−2.48)	(−1.97)	(−2.26)
β_{MKTB}		0.324***	0.145		0.352***		0.325***	0.091
		(2.88)	(1.19)		(2.90)		(3.24)	(0.74)
β_{DRF}	0.046	0.609**	0.299	0.215	0.263			
	(0.38)	(2.18)	(1.17)	(1.21)	(1.38)			
β_{LRF}	0.002	0.184**	0.095	−0.065	−0.070			
	(0.04)	(2.05)	(1.12)	(−0.86)	(−0.93)			
β_{CRF}	−0.160	0.086	−0.027	−0.211	−0.186			
	(−0.67)	(0.29)	(−0.09)	(−0.78)	(−0.70)			
β_{DEF}						−0.161	0.078	−0.088
						(−1.19)	(0.52)	(−0.54)
β_{TERM}						0.370	0.530*	0.353
						(1.28)	(1.93)	(1.45)
β_{MOMB}						−0.030	−0.153	−0.120
						(−0.24)	(−1.04)	(−0.82)
β_{LIQB}						0.023	−0.217	−0.045
						(0.15)	(−1.23)	(−0.29)
Constant	0.158	0.182*	0.138	0.150	0.145	0.189***	0.193***	0.178***
	(1.47)	(1.91)	(1.35)	(1.43)	(1.54)	(3.29)	(3.53)	(3.21)
N	549,016	549,016	549,016	549,016	549,016	475,287	475,287	475,287
Adjusted R^2	0.199	0.199	0.206	0.199	0.201	0.193	0.192	0.200