A Credit-Risk Explanation for Momentum*

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Abstract

We develop a parsimonious rational explanation for momentum based on a structural credit-risk model augmented with implied stochastic volatility. In this framework, equity's option-like payoff generates a trade-off between leverage and convexity effects, producing momentum when the convexity channel dominates. The theory yields a simple closed-form condition for momentum in equities and bonds and implies stronger momentum for firms with higher volatility and leverage, matching key empirical patterns. In U.S. equities, the prediction is supported in the data, with momentum confined to firms satisfying the condition and returns increasing monotonically in its strength. The model predicts little scope for broad momentum in corporate bonds, which is confirmed in the data. Thus, a single structural mechanism in capital structure organizes momentum across assets.

Keywords: Momentum, convexity, implied stochastic volatility

JEL: G12, G13

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1 Introduction

More than three decades after the seminal study of Jegadeesh and Titman (1993), momentum—the tendency of past winners to outperform past losers in securities markets—remains one of the most enduring and pervasive asset pricing anomalies. Momentum is the subject of a voluminous body of research; it has also become highly popular in the investment industry as a core ingredient of "quant" strategies and technical trading rules, and momentum–index trackers are available from the major mutual fund firms.[1]

Despite this extensive attention among academics and practitioners, there is little consensus on the economic mechanism underlying momentum. We propose a novel, parsimonious explanation for momentum that matches key stylized facts documented in the empirical literature and addresses several outstanding challenges. Our explanation builds on a structural credit-risk model in the spirit of Merton (1974), augmented with implied stochastic volatility (Aït-Sahalia, Li and Li, 2020; Carr and Wu, 2020). Without specifying the exact risk factors, this flexible approach summarizes a broad set of sources of market incompleteness, such as stochastic volatility and jumps, in a single variable while allowing for analytical tractability. We find that momentum returns arise in this model as a consequence of equity's option-like payoff, and that the magnitude of momentum returns simulated by the model closely matches that observed in the data. We further derive a simple closed-form condition that characterizes which firms are expected to drive momentum in the data, and we find strong empirical support for this prediction in tests on

[1] Survey evidence suggests that 15% of U.S. asset managers rely on momentum in some form Smith, Faugère and Wang (2013); Swaminathan (2010). BlackRock, Fidelity, and Vanguard market funds tracking the U.S. momentum factor, and ETFdb.com lists 43 momentum ETFs available to U.S. investors, for a total AUM of $14 bn as of March 2019.

U.S. equities and corporate bonds. We also explore explanations for momentum by studying the joint behavior of equity and bond momentum for the same firm. Lastly, we develop an enhanced momentum strategy with cumulative returns more than ten times larger than those based on the standard momentum and we show that the fraction of firms satisfying our condition is a strong predictor of momentum crashes.

The economic mechanism underlying our result is that equity is a convex claim on total assets, which implies that, even if total assets returns are iid, equity returns are not. Under the Merton (1974) framework augmented with implied stochastic volatility (Aït-Sahalia et al., 2020; Carr and Wu, 2020), two effects drive equity returns. The first one is the leverage effect: a low realization of the return makes equity riskier, raising the expected return. The second one is the convexity effect: a low realization of the return takes equity to a region where it is more convex; as a result, the implied stochastic volatility has a more positive impact on equity valuation, lowering the expected return through its negative risk premium. When the convexity effect dominates, therefore, following negative returns the expected return on equity is lower—i.e., we expect momentum.

Our model differs from existing rational settings based on convexity or stochastic volatility that give rise to momentum. First, Sagi and Seasholes (2007) and Garlappi and Yan (2011) show that convexity present in the equity of firms with risky growth options or high shareholders' recovery value can generate autocorrelation in equity returns and momentum. Additionally, in Sagi and Seasholes (2007), firms are effectively unlevered. While in these papers the value of the firm is modeled as a function of a mean-reverting price of their output, our setting shows how implied stochastic volatility can give rise to convexity and momentum without requiring the assumption of mean reversion. Second, recent studies present empirical evidence of the link between stochastic volatility risk and momentum (e.g., Campbell, Giglio, Polk and Turley, 2020; Sichert, 2024). In our model, equity is a levered call on firm assets with stochastic implied variance governing priced sources of market incompletness. Equity is convex because a shock to implied variance raises the dispersion of future asset values. As shareholders are protected on the downside by limited liability, those shocks increase expected returns. Our paper establishes a necessary closed-form condition, under which the convexity effect governed by implied stochastic volatility dominates and equity displays momentum, but simultaneously constrains the joint behavior of equity and debt.

We articulate our analysis in three parts. First, we derive a necessary condition for momentum ("momentum condition" henceforth) from the Merton (1974) model with implied stochastic volatility. The condition relates the sensitivities of the value of equity to changes in the value of total assets (leverage effect) and implied stochastic volatility (convexity effect) with their corresponding risk premia. We show that the condition is satisfied when the convexity effect dominates over the leverage effect. Despite its simplicity, this framework is very flexible and can generate a rich set of testable predictions; for instance, we obtain similar conditions for momentum in corporate debt.

We run simulations based on the Merton model augmented with implied stochastic volatility. We find that, under realistic parameter choices, the model produces momentum returns that are close in magnitude to those reported in the literature. Jegadeesh and Titman (1993) document returns of around 60-70 bps per month (7.2%-8.4% in annual terms) on their momentum strategy. Assuming identical firms that only differ in their debt-to-assets ratio, we obtain simulated monthly momentum returns of 6.6% in annual term.

The simulation exercise also reveals that the model can replicate well-known stylized facts from the literature. For instance, Zhang (2006) finds that momentum tends to be stronger among firms with higher variance. Our simulation indicates that too, with momentum returns ranging from 4.6% to 14.5% p.a. over a range of average asset variances from 5% to 25%. Similarly, Avramov, Chordia, Jostova and Philipov (2007) document that momentum returns are concentrated among firms with higher credit risk. Our simulations also highlight that momentum only occurs if some firms have high credit risk (high leverage). In sum: the theory indicates that the Merton model that features implied stochastic volatility can generate momentum returns; the simulation evidence shows that those returns quantitatively match the existing empirical facts.

Third, we test our predictions on actual data. The model provides a straightforward testable restriction: We should only observe momentum among stocks that satisfy the momentum condition. We sort CRSP stocks into decile portfolios based on prior returns, separating those that satisfy the momentum condition and those that do not, and we compute winners-minus-losers portfolio returns for the two groups. We find that momentum returns among stocks most strongly satisfying the momentum condition exceed the returns among stocks that do not satisfy it by 60 to 100 bps per month (7 - 12% in annualized terms) depending on the risk adjustment. Among stocks that do not satisfy the condition, winners-minus-losers returns are small and mostly insignificant. This result supports the predictions from the model. It is also robust to controlling for a number of variables that have been associated with momentum in Fama-MacBeth regressions.

We test the predictions of the model in three further settings. First, we study momentum in corporate bond returns using the 2002-2024 TRACE sample filtered following Dick-Nielsen, Feldhütter, Pedersen and Stolborg (2025). Our model predicts that under the empirically motivated parametrization we apply, we should not observe any overall momentum in bonds. Our theory also sheds light on why momentum could generally be difficult to obtain in corporate bonds and it could only exists under strict parameter assumptions. Empirically, even though evidence of corporate bond momentum has been previously documented by Jostova, Nikolova, Philipov and Stahel (2013), recent work by Dick-Nielsen et al. (2025) using a novel filtered bond return database documents no significant aggregate momentum in bonds. Consistent with our theory, we find that overall momentum is absent in U.S. corporate bonds.

Our framework delivers joint predictions for equity and bond returns at the firm level: with a single price of risk for implied variance, the same shock that can generate momentum in equity necessarily implies reversals, rather than momentum, in the firm's debt. Consequently, away from deep distress and for extremely short maturities, it is effectively impossible in the model to observe simultaneous momentum in equity and bonds for the same firm. Therefore, to test whether momentum can be explained by a single priced risk factor, we split the sample of firms for which we have bond returns into groups based on the equity momentum condition.We find that past equity returns significantly predict firm-level bond returns only in the groups of firms where, according to the theoretical predictions of our model, equity momentum is most prevalent. This is in line with recent empirical findings that equity momentum predicts bond returns (Dick-Nielsen et al., 2025), and suggests that there are either (i) more priced risks or (ii) frictional forces, such as market segmentation or demand effects, that move both securities together.[2]

Second, in the next draft of the paper, we plan to analyze momentum strategies formed on Japanese stocks. Japan has long stood out as an anomaly within the anomaly: It is the only major stock market where momentum appears to be not profitable (Asness, 2011; Chui, Titman and Wei, 2010; Fama and French, 2012; Griffin, Ji and Martin, 2003; Rouwenhorst, 1998). For that reason, it presents an important challenge for any study that aims to explain momentum.

Third, also in the next draft of our paper, we plan to conduct a further test looking at momentum in index, currency, and commodity futures (as Moskowitz, Ooi and Pedersen (2012)), exploiting a momentum condition in futures analogous to the one we develop for stocks.

Our work makes three main contributions. First, it contributes to the literature on momentum. Starting with the seminal study of Jegadeesh and Titman (1993), numerous papers have documented the pervasiveness of momentum, across international equity markets (e.g. Rouwenhorst (1998) and many others), corporate bonds (Jostova et al., 2013), and indexes and commodities (Asness, Moskowitz and Pedersen, 2013). Along with the growing empirical evidence, a large literature has developed seeking to explain momentum, appealing to rational or behavioral arguments (see Jegadeesh and Titman (2011) for a review). Our contribution is to provide a simple, tractable model that captures the main stylized facts about momentum that have been documented in the literature. In particular, the Merton-model framework we propose unifies the existence of momentum in multiple asset classes, several cross-sectional patterns in momentum returns, as well as the existence of both cross-sectional and time-series momentum.

[2] Collin-Dufresne, Junge and Trolle (2024) also find that equity and credit markets are not fully integrated.

Second, and more broadly, our paper relates to the asset pricing literature that seeks to explain the cross-section of stock returns (Fama and French, 1993, 2012, 2016, 2017; Griffin, 2002; Hou, Andrew and Kho, 2011). Several recent studies have criticized the proliferation of "anomaly" papers, finding that many fail to replicate out-of-sample, and arguing for more conservative statistical testing approaches as a possible solution (Harvey, Liu and Zhu, 2016; Hou, Xue and Zhang, 2020; Linnainmaa and Roberts, 2018). We focus on momentum, one anomaly that is generally considered robust. Our results suggest that in fact it may not be an anomaly, and that it can be reconciled with rational investor behavior and absence of arbitrage opportunities in the context of the Merton (1974) model.

Third, our paper contributes to the literature on structural models of credit risk, which Merton (1974) effectively launched (Black and Cox, 1976; Friewald, Wagner and Zechner, 2014; Leland, 1994; Leland and Toft, 1996; Longstaff and Schwartz, 1995; Schaefer and Strebulaev, 2008). We establish a novel link between that literature and momentum in financial markets. More recently, Zhang, Zhou and Zhu (2009), Du, Elkamhi and Ericsson (2019), Bandi, Fusari and Reno (2023), or Collin-Dufresne et al. (2024) use models of credit risk with additional sources of risk such as jumps or stochastic volatility. In contrast, we use recent advancements from the equity option literature that uses implied volatility as a summary statistic that captures all risks outside the Black and Scholes (1973) and Merton (1974) world. Those papers include, among others, Carr and Wu (2020) or Aït-Sahalia et al. (2020).

2 Structural model

2.1 Framework

In the Merton (1974) model, equity is valued as a long-term European call option on the firm's total assets, with the strike price equal to the face value of outstanding debt. Shareholders receive a residual claim only if asset values exceed liabilities at maturity, leading to an option-like payoff structure. Correspondingly, debt is valued as a risk-free bond minus the value of a put option on the firm's assets, reflecting the possibility of default. Both equity and debt values are thus sensitive to the level and volatility of firm assets, imparting leveraged exposure to their dynamics.

The Merton approach typically begins by modeling the firm's asset dynamics as geometric Brownian motion, implying that the expected *simple* return in equity is linear in the asset's drift.[3] Hence, in order to create momentum in expected *simple* returns, the model requires additional sources of risks that cannot be spanned by dynamically trading the underlying, making the market incomplete. Such risk may be stochastic asset volatility and asset price jumps, which have been shown to be important for accurately capturing market prices, particularly in the context of equity options (Heston, 1993; Merton, 1976) and credit risks (Du et al., 2019; Zhang et al., 2009).

However, extending the Merton (1974) model to include those sources of market incompleteness often comes at the cost of analytical tractability and fail to price long-term option prices with sufficient accuracy (Carr and Wu, 2020). To address these limitations, Carr and Wu (2020) propose a top-down valuation approach that connects the value of options to their daily profit and loss attribution, without

[3] In contrast, the expected *log* return is also a function of the asset's volatility.

requiring a full specification of asset dynamics. The method leverages the Black-Scholes-Merton (BSM) pricing formula,

$$E_t = A_t \Phi \left(\frac{\log(A_t/Fe^{-r\tau}) + \frac{V_{t,F}}{2}\tau}{\sqrt{V_{t,F}}\,\sqrt{\tau}} \right) - Fe^{-r\tau} \Phi \left(\frac{\log(A_t/Fe^{-r\tau}) - \frac{V_{t,F}}{2}\tau}{\sqrt{V_{t,F}}\,\sqrt{\tau}} \right), \quad (1)$$

and interprets the implied volatility $\sqrt{V_{t,F}}$ as a summary statistic that captures all pricing-relevant risks (and other violations of the BSM assumptions). Each firm issues a single class of debt, a zero-coupon bond with face value F and maturity date τ.

The framework does not assume that the BSM model is true; instead, it uses the pricing equation as a mapping between observed prices and the risks they reflect, placing implied volatility at the center of the valuation process in a manner analogous to Aït-Sahalia et al. (2020). This approach has several advantages. First, it preserves closed-form pricing expressions. Second, it simplifies empirical implementation, as it only requires estimates of implied volatility. Third, it allows for flexibility in specifying the dynamics of implied volatility to mimic known structural models. A potential drawback, however, is that it offers less structural interpretability; specifically, it does not provide a clean decomposition of individual risk sources and their contribution to risk premiums.

The central idea of Carr and Wu (2020) is that the instantaneous change in equity, denoted by $E_t(A_t, F, V_{t,F}, \tau)$, can be approximated via a second-order Taylor expansion:

$$\begin{aligned} dE_t = &\frac{\partial E_t}{\partial A_t}\, dA_t + \frac{\partial E_t}{\partial t}\, dt + \frac{\partial E_t}{\partial V_{t,F}}\, dV_{t,F} + \frac{1}{2}\frac{\partial^2 E_t}{\partial A_t^2}\,(dA_t)^2 \\ &+ \frac{1}{2}\frac{\partial^2 E_t}{\partial V_{t,F}^2}\,(dV_{t,F})^2 + \frac{\partial^2 E_t}{\partial A_t \partial V_{t,F}}\, dA_t\, dV_{t,F} + \text{Asset Jumps}. \end{aligned} \quad (2)$$

This expansion is accurate to second order and thus introduces an approximation error of lower order than the typical investment horizon (Carr and Wu, 2020). The partial derivatives in the expression correspond to well-known option Greeks that measure sensitivities to underlying inputs.[4] To analyze risk premia, we consider the difference between the physical ($\mathbb{P}$) and risk-neutral ($\mathbb{Q}$) expectations of (2), yielding:

$$\begin{aligned}&\frac{\partial E_t}{\partial A_t}(\mu(t)-r(t))+\frac{\partial E_t}{\partial V_{t,F}}(\mu_V^{\mathbb{P}}(t)-\mu_V^{\mathbb{Q}}(t))+\frac{1}{2}\frac{\partial^2 E_t}{\partial A_t^2}(\sigma_A^{2,\mathbb{P}}(t)-\sigma_A^{2,\mathbb{Q}}(t))\\&+\frac{1}{2}\frac{\partial^2 E_t}{\partial V_{t,F}^2}(\sigma_V^{2,\mathbb{P}}(t)-\sigma_V^{2,\mathbb{Q}}(t))+\frac{\partial^2 E_t}{\partial A_t\partial V_{t,F}}(\gamma^{\mathbb{P}}(t)-\gamma^{\mathbb{Q}}(t))+\mathrm{JP(t)},\end{aligned} \tag{3}$$

where $\mu(t)$ and $\sigma_A(t)$ denote the (potentially) time-varying drift and volatility of total assets, $\mu_V(t)$ and $\sigma_V(t)$ are the drift and volatility of implied variance, $\gamma(t)$ captures the instantaneous correlation between assets and implied variance, and $JP(t)$ the premium for jumps. Expression (3) is model-free and general.

To make the expression operational, we need to specify the dynamics of A_t and $V_{t,F}$. A number of modeling choices emerge in this context. First, one must decide between a consistent specification where implied variance $V_{t,F}$ is linked to underlying state variables, or an ad hoc specification where it is modeled directly. The former offers conceptual coherence but may require additional terms in the representation of expected returns. We will therefore focus on modelling implied variance directly, similar to the literature on pricing options on stock market variance.[5] Second, one must choose whether implied variance is modeled at the strike level ($V_{t,F}$) or aggregated at the firm level (V_t); for empirical tractability, we adopt the latter.

[4] Note that the sensitivities with respect to $V_{t,F}$ have to be expressed in terms of variance, not volatility.

[5] For instance, Mencía and Sentana (2013) assume an exogenous process for variance when pricing VIX options instead of deriving the VIX from the underlying stock return dynamics.

Finally, the particular specifications of the dynamics of the state variables A_t and V_t determine which risk premia appear in (3) and how they are interpreted.

2.2 Momentum in equity

We begin by specifying a model in which the implied variance V_t resembles time-varying asset variance in the spirit of Heston (1993). Under the physical measure $\mathbb{P}$, the dynamics are given by:

$$\begin{aligned} \frac{dA_t}{A_t} &= \mu\, dt + \sigma_A\, dW_t^{1,\mathbb{P}}, \\ dV_t &= \kappa(\theta - V_t)\, dt + \sigma_V \sqrt{V_t}\, dW_t^{2,\mathbb{P}}, \end{aligned}$$

where u is the expected return on the firm's assets, κ the mean-reversion speed, and θ the mean-reversion level of implied volatility. σ and σ_{IV} are volatility parameters. The Brownian shocks are correlated via ρ. Under the risk-neutral measure $\mathbb{Q}$, the dynamics evolve as

$$\begin{aligned} \frac{dA_t}{A_t} &= r\, dt + \sigma_A\, dW_t^{1,\mathbb{Q}}, \\ dV_t &= \kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}} - V_t)\, dt + \sigma_V \sqrt{V_t}\, dW_t^{2,\mathbb{Q}}, \end{aligned}$$

where $\kappa^{\mathbb{Q}} = \kappa + \lambda_V$ and $\theta^{\mathbb{Q}} = \frac{\kappa\theta}{\kappa+\lambda_V}$. The parameter λ_V is the price of risk. We impose the same correlation ρ under the risk-neutral measure.

The setup of the model is different from the standard approach in which assets have a time-varying variance (e.g., Du et al. (2019), Bandi et al. (2023)). In our setup V_t is not the time-varying asset variance (the variance of assets is described with σ_A) but rather captures compensation for all sources of market incompletness.

This could, in fact, be stochastic asset variance, asset jumps, higher moments, liquidity, demand effects, or model errors, but does not have to be just asset-variance risk. However, since we correlate the Brownian shocks via ρ, those sources of market incompleteness will also be reflected in the value of assets. Put differently, the same underlying economic disturbance that changes risk, prices of risk, and other considerations also impacts assets. For instance, a discount rate shock would increase V_t as $dZ_t > 0$. Since $\rho < 0$, the higher discount rates decrease the value of assets.

Since the diffusion terms and correlations are identical under both measures, the risk premium (the differences between $\mathbb{P}$ and $\mathbb{Q}$) lie in the drifts of the processes. Inserting the model dynamics into equation (3), the expression simplifies to:

$$\mathbb{E}_t^{\mathbb{P}}[dE_t] - \mathbb{E}_t^{\mathbb{Q}}[dE_t] = (E_A A_t(\mu - r) + E_V V_t \lambda_V)\, dt, \tag{4}$$

where E_A and E_V are partial derivatives with respect to assets and implied variance. Hence, the expected change in equity consist of a leverage premium term $E_A A_t(\mu - r)$ and a convexity premium term $E_V V_t \lambda_V$. Substituting $\mathbb{E}_t^{\mathbb{Q}}[dE_t] = rE_t dt$ and dividing (4) by E_t, we get the expected simple equity return

$$g_t = \frac{\mathbb{E}_t^{\mathbb{P}}[dE_t]/E_t}{dt} = r + \eta_t^A(\mu - r) + \eta_t^V \lambda_V, \tag{5}$$

where $\eta_t^A = E_A \frac{A_t}{E_t}$ and $\eta_t^V = E_V \frac{V_t}{E_t}$ measure the percentage change in the value of equity associated with a 1% change in the value of assets and implied variance, respectively.

Momentum is commonly defined as a positive covariance between past and future returns. For our model, we follow the definition of Sagi and Seasholes (2007) and characterise momentum with the conditional covariance between changes in expected and realized returns. If the covariance is positive, higher (lower) realized returns increase (decrease) expected returns. The increase (decrease) in expected returns is the signal to buy (sell) the stock.

Formally, the change in expected returns is given by

$$dg_t = g_A \sigma_A A_t dW_t^1 + g_V \sigma_V \sqrt{V_t} dW_t^2 + O(dt), \tag{6}$$

where $g_A = \frac{\partial \eta_t^A}{\partial A_t}(\mu - r) + \frac{\partial \eta_t^V}{\partial A_t}\lambda_V$ and $g_V = \frac{\partial \eta_t^A}{\partial V_t}(\mu - r) + \frac{\partial \eta_t^V}{\partial V_t}\lambda_V$. The term $O(dt)$ is the drift that collects all dt terms. The realized return is given by

$$r_t = \frac{1}{E_t}(E_A \sigma_A A_t dW_t^1 + E_V \sigma_V \sqrt{V_t} dW_t^2 + O(dt)). \tag{7}$$

At order dt, only the martingale componets covary. Therefore, the covariance is

$$\frac{\mathrm{Cov}_t\left(dg_t, r_t\right)}{dt} = \frac{1}{E_t}\left(g_A E_A \sigma_A^2 A_t^2 + g_V E_V \sigma_V^2 V_t + \rho \sigma_A \sigma_V A_t \sqrt{V_t}(g_A E_V + g_V E_A)\right) \tag{8}$$

because $(dt)^2 = 0$, $(dt dW_t) = 0$, $(dW_t)^2 = dt$, and $(dW_t^1 dW_t^2) = \rho$. Thus, the condition for momentum is that

$$\mathrm{Cov}_t\left(dg_t, r_t\right) > 0. \tag{9}$$

Appendix A gives analytical expressions for $\frac{\partial \eta_t^A}{\partial A_t}$, $\frac{\partial \eta_t^V}{\partial A_t}$, $\frac{\partial \eta_t^A}{\partial V_t}$, and shows that the partial derivatives are strictly negative. $\frac{\partial \eta_t^V}{\partial V_t}$ can have either sign. It is generally negative for very high variance states but more likely to become positive for low-levered firms ($A \gg F$). As the asset risk premium $(\mu - r)$ is positive, the contribution of $\frac{\partial \eta_t^A}{\partial A_t}$ and $\frac{\partial \eta_t^A}{\partial V_t}$ on expected returns is generally negative (leverage effect). As $\lambda_V < 0$, meaning that investors are willing to pay to hedge against risks such as stochastic variance, the contribution of $\frac{\partial \eta_t^V}{\partial A_t}$ is positive (convexity effect).[6] The effect of $\frac{\partial \eta_t^V}{\partial V_t}$ is amibigous and depends on the leverage and variance of the firm.

We analyze $\text{Cov}_t\left(dg_t, r_t\right)$ as a function of leverage (F/A_t) and variance V_t in Figure 1. It shows that both dimensions play a vital role in whether a firm exhibits momentum. Firms that are relatively safe in terms of leverage (low leverage) will only have momentum in expected returns if the implied variance is high, while highly levered firms will almost always have momentum. Put differently, the leverage effect will dominate the convexity effect for low-levered and low-variance firms. The convexity effect dominates for high risk firms (high leverage and/or high variance).

As a second step in our analysis, we simulate the model to assess if it is capable of producing momentum returns of similar magnitude as those documented in the literature. We model 100,000 firms that have identical total assets A_0 of 100 and implied variance of V_0 of 7% at the start. We impose heterogeneity in the leverage of the firms and uniformly draw the level of debt F from the range [10,90]. The price of asset risk $\mu - r$ is 4% and the price of implied variance risk λ_V is -1.5 (Zhang et al., 2009). The time to maturity is fixed at $\tau = 3$ (Doshi, Jacobs, Kumar and Rabinovitch, 2019), which assumes that firms continiously roll over their debt. The other parameters are $\sigma_A = 0.1$, $\sigma_V = 0.2$, $\rho = -0.7$, $\kappa^{\mathbb{P}} = 3$, $\theta^{\mathbb{P}} = 0.05$, which are in-line with estimates from Bandi et al. (2023), Du et al. (2019), and Collin-Dufresne et al. (2024).

To test the model, we implement a similar strategy as in the empirical momentum literatrue. We first simulate five years of daily paths of the state variables A_t and V_t and price equity with Equation (1). Next, we aggregate the realizations to monthly

[6] A large literature documents a negative market price of variance risk, e.g., Bollerslev, Tauchen and Zhou (2009) or Carr and Wu (2009).

and sort firms i) into deciles based on their past 12 month equity returns and ii) if $\mathrm{Cov}_t(dg_t, r_t) > 0$. Lastly, we calculate the next month's equity return.

The results are reported in Table 1. We show the mean, standard deviation, and selected percentiles of the month-ahead returns for each decile portfolio (formed on past twelve-month returns, conditional on $\mathrm{Cov}(dg_t, dE_t) > 0$). The loser portfolio earns about 87 bps per month, while the winner portfolio earns about 141 bps per month, implying a long–short momentum return of 54 bps per month (approximately 6.5% per year). The magnitude is close to the empirical evidence; for example, Jegadeesh and Titman (1993) report momentum profits of roughly 60–70 bps per month. Percentiles of the return distributions shift upward from losers to winners across the board, indicating monotonicity and suggesting that the effect is not driven solely by tails. In Table A.1, we repeat the simulations using the Merton (1974) model and show that the convexity channel is indeed necessary to generate momentum as the spread between the winner and loser portfolio is strongly negative.

Table 2 summarizes how the momentum effect in our model varies with key primitives. Holding everything else fixed, momentum increases with leverage, consistent with the findings of Avramov et al. (2007) that momentum is concentrated among firms with high credit risk (leverage). When we set a common face value $F \in \{30, 50, 60, 80\}$ across firms (Panel A), the loser and winner portfolios have nearly identical means at low leverage ($F = 30$), consistent with the leverage channel offsetting the convexity channel unless implied variance is very high (see Figure 1). Varying the time to maturity τ (Panel B) leaves the long–short spread largely unchanged. Shifting the asset risk premium $(\mu - r)$ (Panel C) moves losers and winners in the same direction, so the momentum spread is relatively stable across specifications. Changing the implied-variance risk premium λ_{IV} (Panel D) yields similarly robust spreads. Finally, increasing either asset volatility σ_A or variance volatility σ_V (Panels E–F) strengthens momentum, in line with the empirical results of Zhang (2006), with a much larger sensitivity to σ_A; for example, $\sigma_A = 0.05$ produces a monthly momentum return of roughly 0.40%, whereas $\sigma_A = 0.30$ produces about 1.40%.

2.3 Momentum in corporate bonds

A firm's total assets is the sum of equity and debt. Hence, we can also price corporate debt via the identity

$$D_t := A_t - E_t. \tag{10}$$

Because corporate debt is the residual between assets and equity, it follows readily that the expected return for debt is given by

$$g_t^D = \frac{\mathbb{E}_t^{\mathbb{P}}[dD_t]/D_t}{dt} = r + \zeta_t^A(\mu - r) + \zeta_t^V \lambda_V, \tag{11}$$

with the bond's elasticity to total assets $\zeta_t^A = \frac{D_A A_t}{D_t}$ and implied variance $\zeta_t^V = \frac{D_V V_t}{D_t}$. Analogous to equity, there is momentum in bond returns if the covariance between realized returns and changes in expected bond returns is positive. The realized return on debt is $r_t^D = \frac{1}{D_t}\big(D_A dA_t + D_V dV_t\big) + O(dt)$, and the change in expected bond returns is given by

$$dg_t^D = g_A^D, dA_t + g_V^D, dV_t + O(dt), \tag{12}$$

with

$$g_A^D = \frac{\partial \zeta_t^A}{\partial A_t}(\mu - r) + \frac{\partial \zeta_t^V}{\partial A_t}\lambda_V, \tag{13}$$

$$g_V^D = \frac{\partial \zeta_t^A}{\partial V_t}(\mu - r) + \frac{\partial \zeta_t^V}{\partial V_t}\lambda_V, \tag{14}$$

The conditional covariance is

$$\frac{\mathrm{Cov}_t(dg_t^D, r_t^D)}{dt} = \frac{1}{D_t}\Big[g_A^D D_A \sigma_A^2 A_t^2 + g_V^D D_V \sigma_V^2 V_t + \rho \sigma_A \sigma_V A_t \sqrt{V_t}\big(g_A^D D_V + g_V^D D_A\big)\Big]. \tag{15}$$

Hence, we expect momentum in bonds when $\mathrm{Cov}_t(dg_t^D, r_t^D) > 0$. As Equation (10) ties the value of debt to equity, we can express $D_A = 1 - E_A$ and $D_V = -E_V$. It is unlikely that the bond conditional covariance $\mathrm{Cov}_t(dg_t^D, r_t^D)$ is positive when the variance risk premium and asset–variance correlation are negative. A positive volatility shock tightens financing conditions and raises perceived default risk, so credit spreads widen and the required (expected) return rises. At the same time, the bond price will fall and realized returns are negative. With a negative asset–variance correlation, higher volatility reduces asset values, and the effect is amplified. The only force that can offset the negative volatility and cross effects is the leverage channel—good news about firm value lifts the bond because default becomes less likely. However, a bond's upside from asset gains is capped by limited convexity: as the firm gets safer the bond behaves more like a risk-free claim, so additional asset upside changes returns only little. Likewise, when the firm isn't close to default, a lot of the asset improvement is already priced into equity, leaving the bond with relatively little incremental sensitivity. Only in edge cases—near distress (where small asset changes increase default risk significantly) or at very short maturities (when asset news dominates / convexity becomes less important)—does the leverage term become strong enough to materially counteract the volatility-driven behavior.

Figure 2 visualizes the bond momentum condition for three maturities: one month, three months, and three years. In Panel A, where we use the same maturity as for equity, there is no bond momentum regradless of leverage or variance. Panel B shows that with shorter maturity, bond momentum is possible, but only for edge cases. In Panel C, where the maturity is only one month and hence debt has to be paid back relatively soon, highly levered firms exhibit bond momentum. Surprisingly, relatively safe companies can also have momentum in their bonds if maturity is very short. This is because volatility shocks are less important, and changes in expected returns are mainly driven by changes in assets.

2.4 Momentum Spillover

Dick-Nielsen et al. (2025) find that equity momentum can predict bond returns. In our model, this translates to a positive association betwee expected bond returns and realized equity returns. That is,

$$\frac{\mathrm{Cov}_t(dg_t^D, r_t)}{dt} = \frac{1}{E_t}\Big[g_A^D E_A \sigma_A^2 A_t^2 + g_V^D E_V \sigma_V^2 V_t + \rho \sigma_A \sigma_V A_t \sqrt{V_t}\big(g_A^D E_V + g_V^D E_A\big)\Big]. \quad (16)$$

Figure 3 shows a positive association between realized equity and expected bond returns for highly levered firms. In contrast to pure bond momentum, this result is not sensitive to the maturity of debt. Hence, we expect some predictiability of past equity returns for future bond returns.

3 Empirical evidence

In this section we test the predictions from the model of Section 2 on actual data. We test the basic prediction that we should only observe momentum among stocks that satisfy the momentum condition (9) and that momentum should increase in magnitude with the covariance between realized stock returns and changes in expected stock returns. We check the robustness of our baseline findings controlling for a number of potential drivers of momentum in Fama-MacBeth regressions.

3.1 Momentum in U.S. equities

We collect monthly returns on common stocks (share codes 10 and 11) quoted on NYSE, Amex, and NASDAQ from CRSP, and combine them with accounting data from Compustat over the period 1968–2024. In all tests, consistent with Daniel and Moskowitz (2016), we require the firms to have a minimum of eight monthly returns over the past 11 months, skipping the most recent month (the momentum strategy formation period). To attenuate the impact of penny stocks and microcaps, we drop stocks with price below \$1 (Jegadeesh and Titman, 2001) and stocks below the 10^{th} NYSE market capitalization percentile (Fama and French, 2008). To attenuate the impact of outliers, stock returns below the 0.5^{th} percentile and above the 99.5^{th} percentile each month are winsorized.

To obtain an empirical counterpart to our momentum condition (9) we estimate the firm-level inputs from the model of Section 2 using stock return and balance sheet debt data, following the approach of Bharath and Shumway (2008). The authors use historical equity returns to obtain an estimate for the required return on total assets μ_t. They rely on an iterative procedure that starts with an initial value for $\sigma_t = \sigma_E[E_t/(E_t + F)]$ to estimate the market value of assets A_t and the implied log return on assets for each day of the previous year based on the Merton model pricing formula (equation (1)). These implied returns are then used to estimate the new implied μ_t and their standard deviation is the new volatility σ_t. The new σ_t is then plugged back into equation (1) to find A_t and the procedure is iterated until σ_t converges. Consistent with our model we fix the following parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$. These estimates allow us to partition the CRSP universe, in each calendar month, into a subset of stocks for which the momentum condition (9) is satisfied, where we expect momentum, and a subset where the condition fails, where we do not expect momentum.

Figure A.1 plots the percentage of CRSP stocks that satisfy condition (9) over the period 1968–2024. On average, about 15% of stocks meet the condition; but there is considerable time-series variation, with peaks in the 1970s and 2010s and troughs in the 1980s and 2000s. In addition, the average covariance between changes in realized and expected stock returns (equation (8)) in most of the sample years is positive (see Figure 4). Thus, our model suggests that on average we should observe positive momentum in equity, with a few exceptions of reversal or momentum crashes (documented by Daniel and Moskowitz (2016)) when the covariance turns negative. We build on these data in our baseline tests looking at momentum in U.S. equities.

In further checks, we control for a number of stock characteristics that might affect stock returns in general or momentum returns in particular. We include log-market equity, book-to-market, gross profitability ratio, and debt to assets ratio, which we retrieve from the CRSP/Compustat Merged database; share turnover ratio from the CRSP database; an indicator for firms that have a speculative grade credit rating from Standard and Poor's (BBB– or inferior); log-Analyst coverage, and analyst forecast dispersion ratio (standard deviation of analyst EPS forecasts divided by the mean forecast) from the IBES database.

As a first step, we run a test based on simple sorts in the spirit of Cooper, Gutierrez and Hameed (2004). We separate stocks into those that satisfy the momentum condition (9) and those that do not. In particular, those that satisfy the condition have a positive covariance between changes in realized and expected equity returns, and those that do not – a negative covariance. Further, in each subset, at each calendar month t we sort the stocks in three terciles based on the level of that covariance (equation (8)). Within each of the resulting six groups, every month we obtain breakpoints by sorting stocks into deciles based on their return over the period from month $t-12$ to month $t-2$. We compute value-weighted decile portfolio returns from time t to time $t+1$ (skipping month $t-1$), as well as the return on the winners-minus-losers portfolio, long in the 10^{th} decile (highest prior return) and short in the 1^{th} decile (lowest prior return).

Table 3 reports the results. The first "Overall" column reports the average decile portfolio returns as well as the average return on the winners-minus-losers portfolio for the entire CRSP universe.[7] Similar to the findings of the literature (e.g. Daniel and Moskowitz (2016)), we find average winners-minus-losers returns of 98 bps per month (about 12% annualized). Further, we separate the sample of stocks into six groups based on the momentum condition, as described above, and report the difference in winners-minus-losers spreads between them. The results

[7] In this case, the sorting into prior return deciles is not conditional on the momentum condition.

are in line with the predictions developed in Section 2 . Momentum is positive and statistically significant only in Groups 4, 5, and 6, where the momentum condition is satisfied and momentum is indistinguishable from zero in Groups 1, 2, and 3 that do not satisfy our condition. Notably, the spread between winners and losers increases monotonically as the covariance between past stock returns and changes in expected stock returns increases, from 0.493% per month in Group 1 to 1.382% in Group 6. In the online appendix we report the portfolio returns based on independent sorts according ot past returns and the covariance between changes in past and expected equity returns. Consistent with the results based on the sequential sorts (Table A.2), we find that the momentum returns increase monotonically from 0.600% in Group 1 to 2.288% per month in Group 6.

We find similar results when we examine the incercepts on Fama and French (1993, 2016) 3- and 5-factor models for the decile and winners-minus-losers portfolio returns, rather than looking at raw returns. The winners-minus-losers intercepts for stocks that satisfy the momentum condition (Group 6) is 167 bps per month versus 62 bps for stocks that do not satisfy it (Group 1) under the 3-factor model. The intercepts under the 5-factor model are 118 bps in Group 6 and 59 bps in Group 1.

To gauge the robustness of these findings, and given the voluminous empirical literature on momentum, we also check that our condition is not subsumed by the drivers of momentum that have been documented in previous studies. To that end, we run regressions in the spirit of Fama and MacBeth (1973), which allow us to simultaneously control for a large number of candidate drivers of momentum returns.

We structure this test as follows. First, for each stock i and calendar month t, we define the cumulative 12-month prior return on i over the period from $t-12$ to

$t-2$, denoted by $\bar{r}_{it}$. In Table 5, Column (1) we regress the raw return r_{it+1} from time t to $t+1$ on $\bar{r}_{it}$, the covariance between changes in past and expected equity returns (equation (8)) and an interaction term between the two. In Columns (2) and (3) we control for other stock characteristics and alternative potential drivers of momentum identified in the literature. We estimate:

$$r_{it+1} = \alpha + \beta \bar{r}_{it} \times \text{Cov}_{it} + \sum_k \gamma_k x_{kit} + \sum_k \delta_k \bar{r}_{it} \times x_{kit} + \varepsilon_{it}, \tag{17}$$

where x_k are a number of characteristics including: log-market equity, log-book/market ratio, gross profitability, log-debt to assets ratio, log-share turnover ratio, log-analyst coverage, log-analyst forecast dispersion, credit rating, as well as their interactions with $\bar{r}_{it}$, and indicators for industry. These variables reflect stylized facts documented in the literature on momentum, such as the fact that it concentrates among firms with speculative grade credit rating (Avramov et al. (2007)) and high information uncertainty (Zhang (2006)). The regression also includes Fama-French 30 industry indicators. We estimate these regressions as in Fama and MacBeth (1973), i.e. we run a separate regression for each calendar month, and then draw inference by averaging the slope coefficients.

In all specifications the dependent variable is the raw return r_{it+1}. Across all regression model formulations, we find a positive, highly significant coefficient on the interaction term $\bar{r}_{it} \times \text{Cov}_{it}$, consistent with our baseline results. The estimates imply that a 1% higher prior return $\bar{r}$ and one standard deviation increase in covariance are associated with 88 bps higher month $t+1$ return. Notably, for the stocks that do not satisfy the momentum condition in Group 1 the prior return has no significant relationship to future returns, so they do not exhibit any momentum. In sum, these estimates indicate that our baseline result is robust to controlling for a number of potential drivers of momentum.

3.2 Momentum in U.S. corporate bonds

We also run tests for momentum among corporate bonds, based on the condition (equation (**??**)) we discuss in Section 2.3. We take that condition to the data using a sample of U.S. corporate bonds. We use the sample of bonds available on TRACE in the period 2002-2021. To ensure we have a database of clean bond returns for our tests, we use the Corporate bond factors data repository dataset filtered based on the methodology of Dick-Nielsen et al. (2025).

As discussed in Section 2.3, our model predicts that there will not be any momentum in bonds under our empirically motivated parametrization and that bond momentum could only exist under restrictive parameter assumptions. To test this prediction, we empirically estimate the covariance between changes in past bond returns and expected bond returns (equation (15)) implied by our model, where our condition (**??**) predicts bond momentum when the covariance is positive, and its absence otherwise. Figure 5 shows that in the period 1968-2024 the average covariance never exceeds zero, consistent with our theory.[8] Hence, we should not expect any momentum in corporate bonds.

Our momentum portfolio sorts using the U.S. corporate bond data confirm this prediction. We sort raw firm-level and bond-level bond returns into decile portfolios based on their previous returns (from time $t-12$ to $t-2$) and we estimate the performance of long-short momentum portfolios from time t to $t+1$. The results are reported in Table 6. We find no significant overall momentum in both bond-level

[8] Since we can express our bond momentum condition using only stock and accounting level information, we can estimate the model-implied covariance between changes in realized and expected bond returns in the CRSP-Compustat sample period 1968-2024.

bond returns (Column 1) and firm-level (Column 2), which supports the predictions of our model. Thus, our theory sheds some light on why it might be difficult to observe momentum in bonds and while Jostova et al. (2013) find some empirical evidence for it, Dick-Nielsen et al. (2025) find that monthly average momentum returns are close to zero and insignificant.

Prior studies (Dick-Nielsen et al. (2025); Jostova et al. (2013)) find evidence that equity momentum predicts bond returns and momentum in bonds. Our theory also delivers joint testable predictions about equity and bond returns. Thus, as a next step, we check for potential such spillover within the framework of our model. In Table 6, Column (3) we sort raw firm-level bond returns into decile portfolios based on their firms' past equity month $t-12$ to $t-2$ returns and report the holding period bond returns from time t to $t+1$. Overall we find no significant difference between the top and bottom decile portfolios. Once we split the firms in subsamples based on our equity momentum condition (9), however, the effect emerges. Similar to our test for momentum in U.S. equities, in Table 7 we first split our sample in two groups – those that satisfy our equity momentum condition (9) and those that do not. Within each subset we split the firms in three terciles based on the covariance between changes in realized and expected equity returns (equation (8)). In each of the six groups we sort firm-level and bond-level bond returns based on the past $t-12$ to $t-2$ stock returns and firm- or bond-level bond returns.

In Panel A we sort bond-level returns based on their own prior returns and in Panel B we sort firm-level bond returns based on their own prior month $t-12$ to $t-2$ returns. Bond-level momentum returns are predominantly negative throughout the six groups based on equity momentum. Even though we find some positive momentum of about 57–70 bps per month (7–8% annualized) in Groups

5 and 6 that have the highest equity momentum, it is statistically insignificant. In Panel C we find that firm-level bond returns of winners sorted based on past stock returns significantly outperform losers by 87 bps and 84 bps per month (about 10% annualized) in Groups 5 and 6, respectively. The difference between winners and losers is indistinguishable from zero in Groups 1 to 4. These findings suggest that equity momentum predicts bond returns significantly, but only in Groups 5 and 6 that exhibit the largest equity momentum returns based on our model, while momentum in bonds is insignificant even in these groups.

3.3 Enhanced momentum strategy

As explained in Section 3.1, in the online appendix we perform an alternative independent portfolio sort based on past returns and the covariance between realized equity returns and changes in expected equity returns. Since the two independent signals yield higher portfolio returns in Group 6 compared to those based on sequential sorts (2.288% per month vs. 1.382% per month), we base our enhanced momentum strategy on independent sorts. In Figure 6 we report the cumulative returns based on the overall standard momentum strategy vs. enhanced momentum strategy. We find that that despite its volatility our enhanced momentum strategy yields cumulative returns over ten times larger than the cumulative returns of the baseline momentum strategy.

3.4 Momentum crashes

In their seminal paper Daniel and Moskowitz (2016) show that momentum in equities experiences episodes of extreme negative returns, which occur after periods of high volatility when the market rebounds. In Table 8 we show that these momentum crashes are strongly predictable by the lagged fraction of firms that satisfy the momentum condition implied by our model. In Panel A, Columns 1 and 3 we define a momentum crash as an indicator for the bottom 5% of momentum returns and in Columns 2 and 4 – for the bottom 10% of momentum returns. Increasing the fraction of stocks satisfying the momentum condition by 20% raises the momentum crash probability by about 10%. Intuitively, the higher the percentage of stocks satisfying the condition, the more each of them loads on a systematic convexity factor. If market volatility suddenly drops after a period of extreme highs stocks with the strongest loading on the common factor experience the largest positive jumps in their returns. In Panel B we show that losers are likely to be these stocks, as the fraction of firms satisfying our momentum condition positively predicts highest 5% or 10% loser returns. Thus, consistent with Daniel and Moskowitz (2016), in such episodes losers strongly outperform winners and momentum crashes take place.

4 Conclusion

We propose a structural explanation for momentum grounded in the Merton (1974) framework augmented with implied stochastic volatility (Aït-Sahalia et al., 2020; Carr and Wu, 2020). The model highlights a fundamental interaction between leverage and convexity: equity's option-like structure implies that even when total asset returns are independent and identically distributed, equity returns need not be. When the convexity channel, operating through the sensitivity of equity to implied stochastic volatility, dominates the leverage channel, past return realizations lead to predictable variation in expected returns. This condition yields a straightforward, closed-form criterion indicating when momentum should arise. Simulations calibrated to empirically plausible parameters generate momentum profits comparable in magnitude to those documented in the literature and reproduce well-known cross-sectional patterns.

Empirical tests support the model's key predictions. U.S. equity momentum is concentrated precisely among firms that satisfy the condition derived from the structural framework, and the strength of momentum increases with the covariance between past realized returns and changes in expected returns implied by the model. These results are robust to standard risk adjustments and to controls for characteristics previously associated with momentum. Further, we develop an enhanced momentum strategy that yields cumulative returns more than ten times larger than those based on the baseline momentum and we show that the fraction of firms satisfying our condition strongly predicts momentum crashes. In corporate bonds, the model predicts little aggregate momentum under empirically motivated parameter values, a pattern consistent with evidence from clean return data, though equity momentum predicts bond returns but only in subsamples of firms whose equity satisfies the momentum condition. Taken together, the theory and evidence indicate that a Merton-style model with implied stochastic volatility can account for the magnitude, distribution, and cross-sectional variation of momentum, while also explaining when and where momentum should not be expected to occur.

References

Asness, C. S. (2011). Momentum in Japan: The Exception that Proves the Rule, *Journal of Portfolio Management* **37**(4): 67–75.

Asness, C. S., Moskowitz, T. J. and Pedersen, L. H. (2013). Value and Momentum Everywhere, *Journal of Finance* **68**: 929–985.

Avramov, D., Chordia, T., Jostova, G. and Philipov, A. (2007). Momentum and Credit Rating, *Journal of Finance* **62**: 2503–2520.

Aït-Sahalia, Y., Li, C. and Li, C. X. (2020). Implied stochastic volatility models, *Review of Financial Studies* **34**: 394–450.

Bandi, F., Fusari, N. and Reno, R. (2023). Structural Stochastic Volatility, Working paper.

Bharath, S. T. and Shumway, T. (2008). Forecasting Default with the Merton Distance to Default Model, *Review of Financial Studies* **21**(3): 1339–1369.

Black, F. and Cox, J. C. (1976). Valuing Corporate Securities: Some Effects of Bond Indenture Provisions, *Journal of Finance* **31**(2): 351–367.

Black, F. and Scholes, M. (1973). The Pricing of Options and Corporate Liabilities, *Journal of Political Economy* **81**(3): 637–654.

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

Campbell, J. Y., Giglio, S., Polk, C. and Turley, R. (2020). An intertemporal capm with stochastic volatility, *Journal of Financial Economics* **128**: 207–233.

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

Carr, P. and Wu, L. (2020). Option profit and loss attribution and pricing: A new framework, *Journal of Finance* **75**(4): 2271–2316.

Chui, A. C. W., Titman, S. and Wei, K. C. J. (2010). Individualism and Momentum Around the World, *Journal of Finance* **65**: 361–392.

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

Cooper, M. J., Gutierrez, R. C. and Hameed, A. (2004). Market States and Momentum, *Journal of Finance* **59**(3): 1345–1365.

Daniel, K. and Moskowitz, T. J. (2016). Momentum Crashes, *Journal of Financial Economics* **122**: 221–247.

Dick-Nielsen, J., Feldhütter, P., Pedersen, L. H. and Stolborg, C. (2025). Corporate Bond Factors: Replication Failures and a New Framework, *Working paper* .

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

Du, D., Elkamhi, R. and Ericsson, J. (2019). Time-Varying Asset Volatility and the CreditSpread Puzzle, *Journal of Finance* **74**: 1841–1885.

Fama, E. F. and French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* **33**: 3–56.

Fama, E. F. and French, K. R. (2008). Dissecting Anomalies, *Journal of Finance* **63**: 1653–1678.

Fama, E. F. and French, K. R. (2012). Size, Value, and Momentum in International Stock Returns, *Journal of Financial Economics* **105**: 457–472.

Fama, E. F. and French, K. R. (2016). Dissecting Anomalies with a Five-Factor Model, *Review of Financial Studies* **29**(1): 69–103.

Fama, E. F. and French, K. R. (2017). Long-Horizon Returns, Working paper, University of Chicago.

Fama, E. F. and MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* **81**(3): 607–636.

Friewald, N., Wagner, C. and Zechner, J. (2014). The Cross-Section of Credit Risk Premia and Equity Returns, *Journal of Finance* **69**: 2419–2469.

Garlappi, L. and Yan, H. (2011). Financial distress and the cross-section of equity returns.

Griffin, J. M. (2002). Are the Fama and French Factors Global or Country Specific?, *Review of Financial Studies* **15**: 783–803.

Griffin, J. M., Ji, X. and Martin, J. S. (2003). Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole, *Journal of Finance* **58**: 2515–2547.

Harvey, C. R., Liu, Y. and Zhu, H. (2016). . . . And the Cross-Section of Stock Returns, *Review of Financial Studies* **29**: 5–68.

Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options, *The Review of Financial Studies* **6**(2): 327–343.

Hou, K., Andrew, G. and Kho, B.-C. (2011). What Factors Drive Global Stock Returns?, *Review of Financial Studies* **24**: 2527–2574.

Hou, K., Xue, C. and Zhang, L. (2020). Replicating Anomalies, *Review of Financial Studies* **33**(5): 2019–2133.

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock market Efficiency, *Journal of Finance* **48**: 65–91.

Jegadeesh, N. and Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* **56**: 699–720.

Jegadeesh, N. and Titman, S. (2011). Momentum, *Annual Review of Financial Economics* **3**: 493–509.

Jostova, G., Nikolova, S., Philipov, A. and Stahel, C. W. (2013). Momentum in Corporate Bond Returns, *Review of Financial Studies* **26**(7): 1649–1693.

Leland, H. E. (1994). Risky Debt, Bond Covenants and Optimal Capital Structure, *Journal of Finance* **49**: 1213–1252.

Leland, H. E. and Toft, K. B. (1996). Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads, *Journal of Finance* **51**: 987–1019.

Linnainmaa, J. T. and Roberts, M. R. (2018). The History of the Cross-Section of Stock Returns, *Review of Financial Studies* p. forthcoming.

Longstaff, F. A. and Schwartz, E. S. (1995). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt, *Journal of Finance* **50**: 789–819.

Mencía, J. and Sentana, E. (2013). Valuation of vix derivatives, *Journal of Financial Economics* **108**(2): 367–391.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *Journal of Finance* **29**: 449–470.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous, *Journal of Financial Economics* **3**(1): 125–144.

Moskowitz, T. J., Ooi, Y. H. and Pedersen, L. H. (2012). Time-Series Momentum, *Journal of Financial Economics* **104**: 228–250.

Rouwenhorst, K. G. (1998). International Momentum Strategies, *Journal of Finance* **53**: 267–284.

Sagi, J. S. and Seasholes, M. S. (2007). Firm-Specific Attributes and the Cross Section of Momentum, *Journal of Financial Economics* **84**(2): 389–434.

Schaefer, S. M. and Strebulaev, I. (2008). Structural Models of Credit Risk Are Useful: Evidence from Hedge Ratios on Corporate Bonds, *Journal of Financial Economics* **90**: 1–19.

Sichert, T. (2024). A Non-Linear Market Model, *Working paper* .

Smith, D., Faugère, C. and Wang, Y. (2013). Head and Shoulders above the Rest? The Performance of Institutional Portfolio Managers Who Use Technical Analysis, Working Paper.

Swaminathan, B. (2010). Quantitative Money Management: A Practical Application of Behavioral Finance, Working Paper.

Zhang, B. Y., Zhou, H. and Zhu, H. (2009). Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms, *Review of Financial Studies* **22**: 5099–5131.

Zhang, X. F. (2006). Information Uncertainty and Stock Returns, *Journal of Finance* **61**: 105–136.

Appendix

A Expected return sensitivities

The condition for momentum depends on the sensitivities of $\eta_t^A = E_A \frac{A_t}{E_t}$ and $\eta_t^V = E_V \frac{V_t}{E_t}$ with respect to the model's state variables. That is, it depends on $\frac{\partial \eta_t^A}{\partial A_t}$, $\frac{\partial \eta_t^V}{\partial A_t}$, $\frac{\partial \eta_t^A}{\partial V_t}$ and $\frac{\eta_t^V}{\partial V_t}$. We start by proving that $\frac{\partial \eta_t^A}{\partial A_t} < 0$. Define $m = A/Fe^{-r\tau}$ and note that $E_A = \frac{\partial E_t}{\partial A_t} = \Phi(d_1)$ is the standard Black-Scholes delta. Therefore,

$$\eta_t^A = \Phi(d_1)\frac{A_t}{E_t} = \left[\frac{A_t\Phi(d_1) - Ke^{-r\tau}\Phi(d_2)}{A_t\Phi(d_1)}\right]^{-1} = \left[1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right]^{-1}. \tag{18}$$

Hence, we get that

$$\frac{\partial \eta_t^A}{\partial A_t} = \frac{E_A + A_t E_{AA}}{E_t} - \frac{A_t E_A^2}{E_t^2} \tag{19}$$

$$= \frac{\partial}{\partial A_t}\left(\frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right) \tag{20}$$

$$= \frac{Fe^{-r\tau}}{A_t} \times \left[\frac{\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1)}{A_t(\Phi(d_1))^2 V_t\sqrt{\tau}} - \frac{\Phi(d_2)}{A_t\Phi(d_1)}\right] \tag{21}$$

$$= \frac{1}{m} \times \frac{\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1) - \Phi(d_1)\Phi(d_2)V_t\sqrt{\tau}}{A_t(\Phi(d_1))^2 V_t\sqrt{\tau}}, \tag{22}$$

where we denote $d_1 \equiv \frac{1}{V_t\sqrt{\tau}}[\ln(m) + \frac{V_t^2}{2}\tau]$, $d_2 \equiv d_1 - V_t\sqrt{\tau}$, and $\Phi(\cdot)$ is the normal cdf while $\varphi(\cdot)$ denotes the normal pdf. E_{AA} is the second partial derivative of equity with respect to assets. Therefore:

$$\frac{\partial \eta_{A,t}}{\partial A_t} = \frac{\partial}{\partial A_t}\left[\left(1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right)^{-1}\right] = \frac{\frac{1}{m} \times \frac{\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1) - \Phi(d_1)\Phi(d_2)V_t\sqrt{\tau}}{A_t\Phi(d_1)^2 V_t\sqrt{\tau}}}{\left(1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right)^2}. \tag{23}$$

Since $1/m > 0$, $A_t\Phi(d_1)^2V_t\sqrt{\tau} > 0$, and $\left(1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right)^2 > 0$, the sign of $\frac{\partial \eta_{A,t}}{\partial A_t}$ depends on the sign of $\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1) - \Phi(d_1)\Phi(d_2)V_t\sqrt{\tau}$.

We now factor out $\Phi(d_1)\Phi(d_2) > 0$ and prove that:

$$\frac{\varphi(d_2)}{\Phi(d_2)} - \frac{\varphi(d_1)}{\Phi(d_1)} < V_t\sqrt{\tau} \tag{24}$$

for all d_1 and d_2, so that $\frac{\partial \eta_{A,t}}{\partial A_t} < 0$. For compact notation, let $h(x) \equiv \varphi(x)/\Phi(x)$ and $s \equiv V_t\sqrt{\tau}$. Now $h(d_2) - h(d_1) < s$ as long as $|h'(d)| < 1$ for all d. To see that, note that $|h'(d)| < 1$ implies:

$$\int_{d_2}^{d_1} |h'(x)|dx < \int_{d_2}^{d_1} |1|dx = |d_1| - |d_2| = d_1 - d_2 = s. \tag{25}$$

But then:

$$h(d_2) - h(d_1) = \left|\int_{d_2}^{d_1} h'(x)dx\right| \leq \int_{d_2}^{d_1} |h'(x)|dx < s, \tag{26}$$

where the inequality is the well-known result for the absolute value of a definite integral. Therefore, if $|h'(d)| < 1$, condition (24) will be satisfied.

To show that, we proceed in three steps. First, we show a preliminary result that $h(x) + x > 0$. Second, we use this result to show that $h'(x) < 0$. Third, we prove that $h'(x) > -1$. Then it is guaranteed that $h'(x) \in (-1,\ 0) \subset (-1,\ 1)$.

(i) $h(x) + x > 0$. Define the auxiliary function $g(x) \equiv \varphi(x) + x\Phi(x)$. Using De l'Hopital's rule, $\lim_{x\to-\infty} g(x) = 0$; moreover $g'(x) = -x\varphi(x) + x\varphi(x) + \Phi(x) > 0$. Thus $g(x)$ is 0 for $x \to -\infty$ and increasing thereafter, and therefore it is always positive. But if $g(x) > 0$, then $h(x) + x = g(x)/\Phi(x) > 0$ too.

(ii) $h'(x) < 0$. Since $h(x) > 0$ and $h(x) + x > 0$, it follows that $h'(x) = -h(x)\,[x + h(x)] < 0$.

(iii) $h'(x) + 1 > 0$. Denote $f(x) \equiv \frac{\varphi'(x)}{\varphi(x)}\Phi(x) - \varphi(x) + \frac{\Phi^2(x)}{\varphi(x)}$. Thus:

$$\frac{\varphi(x)}{\Phi^2(x)}f(x) = \frac{\varphi(x)}{\Phi^2(x)}f(x)\left[\frac{\varphi'(x)}{\varphi(x)}\Phi(x) - \varphi(x) + \frac{\Phi^2(x)}{\varphi(x)}\right] = \frac{\varphi'(x)\Phi(x) - \varphi^2(x)}{\Phi^2(x)} = h'(x)+1. \quad (27)$$

Since $\varphi'(x) = -x\varphi(x)$, we have:

$$f'(x) = -\Phi(x) - x\varphi(x) + x\varphi(x) + \frac{2\Phi(x)\varphi(x) + x\Phi^2(x)}{\varphi(x)} = \\ -\Phi(x) + 2\Phi(x) + x\frac{\Phi^2(x)}{\varphi(x)} = \Phi(x)\left[1 + \frac{x}{h(x)}\right]. \quad (28)$$

Because $h(x) > 0$ and $h(x)+x > 0$, $1+\frac{x}{h(x)} > 0$. Furthermore, $\lim_{x\to-\infty} f(x) = 0$. So $f(x)$ is 0 for $x \to -\infty$ and increasing thereafter, and therefore it is always positive. But then $\frac{\phi(x)}{\Phi^2(x)}f(x) = h'(x) + 1 > 0$, and $h'(x) > -1$.

Thus, we have shown that $\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1) - \Phi(d_1)\Phi(d_2)V_t\sqrt{\tau} < 0$ and $\frac{\partial \eta_t^A}{\partial A_t} < 0$.

□

Next, we prove that

$$\frac{\partial \eta_t^V}{\partial A_t} = \frac{V_t(E_{AV}E - E_V E_A)}{E_t^2} < 0. \quad (29)$$

Note that we can express equity's sensitivity to variance, as $E_V = \frac{\partial E_t}{\partial V_t} = A_t\varphi(d_1)\sqrt{\tau}$ and therefore $\eta_t^V = E_V\frac{V_t}{E_t}$ can be written as:

$$\eta_t^V = \frac{A_t}{E_t}\varphi(d_1)V_t\sqrt{\tau} = \eta_t^A\frac{\varphi(d_1)}{\Phi(d_1)}V_t\sqrt{\tau}. \quad (30)$$

Hence, we can write the condition $\frac{\partial \eta_t^V}{\partial A_t} < 0$ as follows:

$$\begin{aligned} \frac{\partial \eta_t^V}{\partial A_t} = \frac{\partial}{\partial A_t} \left(\eta_t^A \frac{\varphi(d_1)}{\Phi(d_1)} V_t \sqrt{\tau} \right) &< 0 \\ \Leftrightarrow V_t \sqrt{\tau} \left(\frac{\partial \eta_t^A}{\partial A_t} \frac{\varphi(d_1)}{\Phi(d_1)} + \eta_t^A \frac{\partial}{\partial A_t} \left(\frac{\varphi(d_1)}{\Phi(d_1)} \right) \right) &< 0 \end{aligned} \tag{31}$$

We know that $V_t \sqrt{\tau} > 0$, $\eta_t^A > 0$, and $\frac{\varphi(d_1)}{\Phi(d_1)} > 0$. Second, we have already proven earlier that $\frac{\partial \eta_t^A}{\partial A_t} < 0$ and $\frac{\partial}{\partial A_t} \left(\frac{\varphi(d_1)}{\Phi(d_1)} \right) = -\frac{\varphi(d_1)}{\Phi(d_1)} \left(d_1 + \frac{\varphi(d_1)}{\Phi(d_1)} \right) \frac{1}{A_t V_t \sqrt{\tau}} < 0$. This is sufficient to confirm that $\frac{\partial \eta_t^V}{\partial A_t} < 0$ is satisfied.

Next, we analyze the sign of $\frac{\partial \eta_t^A}{\partial V_t}$. The derivative is given by

$$\frac{\partial \eta_t^A}{\partial V_t} = \frac{A_t (E_{AV} E - E_V E_A)}{E_t^2} \tag{32}$$

which is the almost the same expression as in (29) other than multiplying by A_t instead of V_t. Since both A_t and V_t are positive, $\frac{\partial \eta_t^A}{\partial V_t}$ has the same sign as $\frac{\partial \eta_t^A}{\partial V_t}$ and is strictly negative.

Lastly, we analyze the sign of $\frac{\partial \eta_t^V}{\partial V_t}$. The derivative is given by

$$\frac{\partial \eta_t^V}{\partial V_t} = \frac{E_V + V_t E_{VV}}{E_t} - \frac{V_t E_V^2}{E_t^2} \tag{33}$$

Pluging in the expressions for the Black-Scholes sensitivities, one can show that $\frac{\partial \eta_t^V}{\partial V_t} > 0$ if

$$\left(e^n \Phi(d_1) - \Phi(d_2) \right) \left(d_1 d_2 + 1 \right) > e^n V_t \sqrt{T} \phi(d_1), \tag{34}$$

with $n = \log \left(\frac{A e^{r\tau}}{K} \right)$. It is negative for very high variance states but more likely to become positive for low-levered firms ($A \gg F$).

Figures and Tables

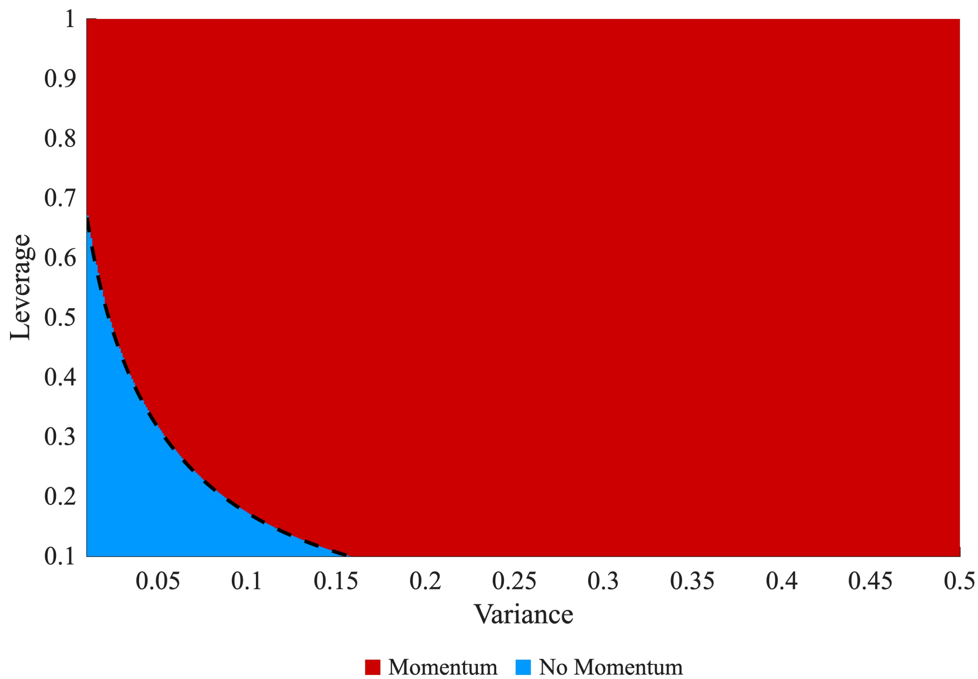

Figure 1. Sensitivity of equity momentum condition
The figure plots the sign of $\mathrm{Cov}_t\,(dg_t, r_t)$ from Equation (8) as a function of leverage F/A_t and variance V_t. The red (blue) area are states where Cov_t is positive (negative), implying momentum (no momentum). We use the following annualized parameters: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, time to maturity $\tau = 3$, and correlation between the assets and implied variance shocks $\rho = -0.7$.

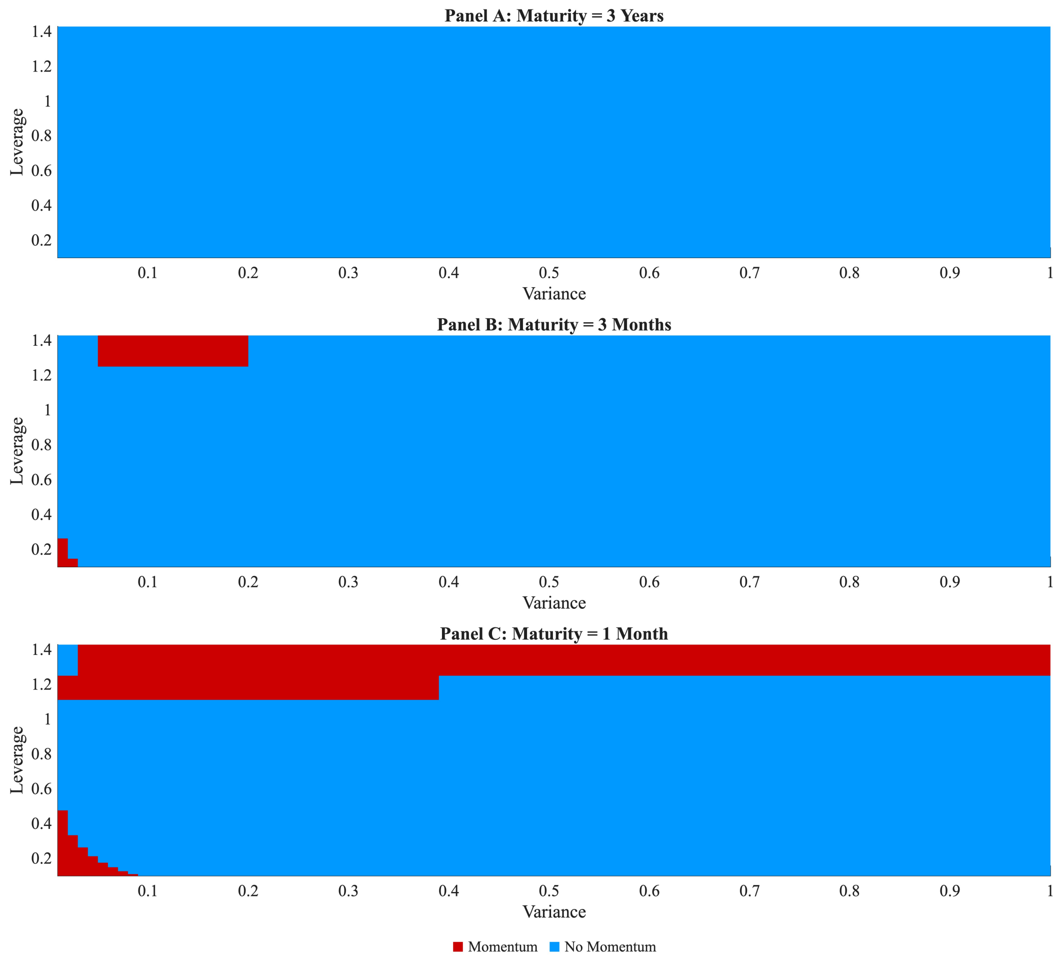

Figure 2. Sensitivity of bond momentum condition
The figure plots the sign of $\text{Cov}_t\left(dg_t^D, r_t^D\right)$ from Equation (15) as a function of leverage F/A_t and variance V_t. The red (blue) area are states where Cov_t is positive (negative), implying momentum (no momentum). Panel A plots the condition for a maturity of three years, Panel B for three months, and Panel C for one month. We use the following annualized parameters: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, time to maturity $\tau = 3$, and correlation between the assets and implied variance shocks $\rho = -0.7$.

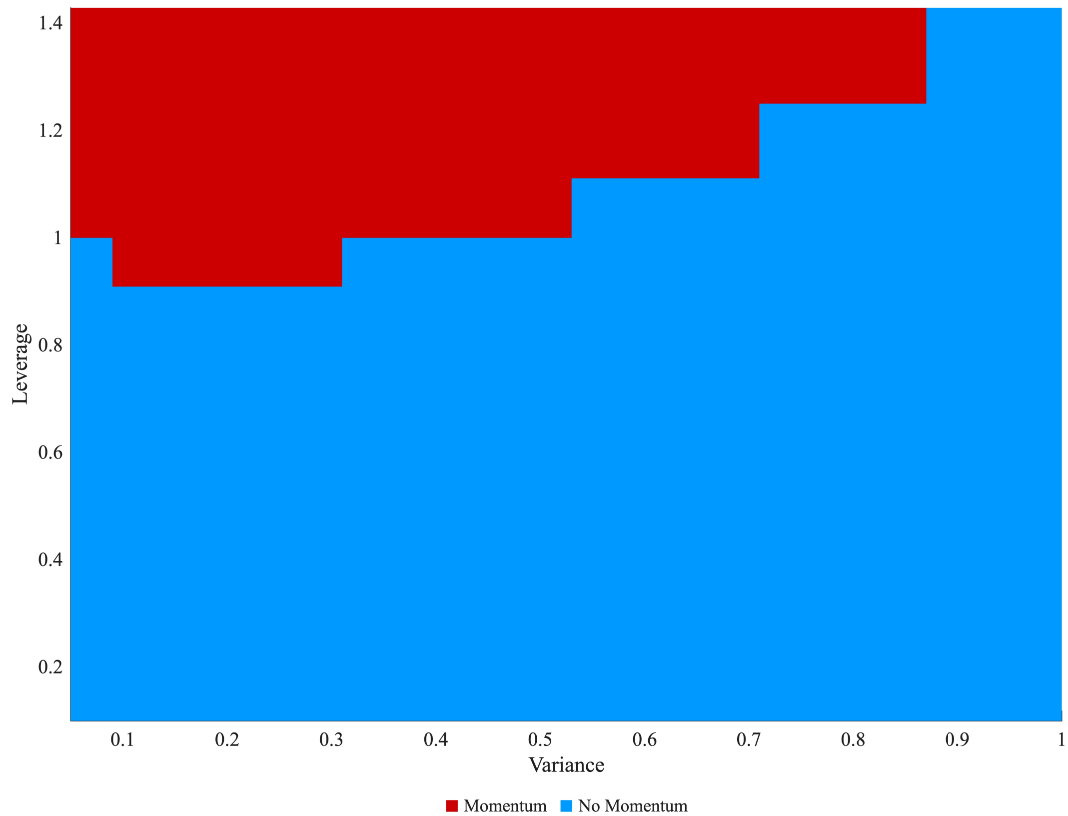

Figure 3. Covariance between past equity and expected bond returns
The figure plots the sign of $\text{Cov}_t\left(dg_t^D, r_t\right)$ from Equation (16) as a function of leverage F/A_t and variance V_t. The red (blue) area are states where Cov_t is positive (negative), implying momentum (no momentum). We use the following annualized parameters: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance shocks $\rho = -0.7$.

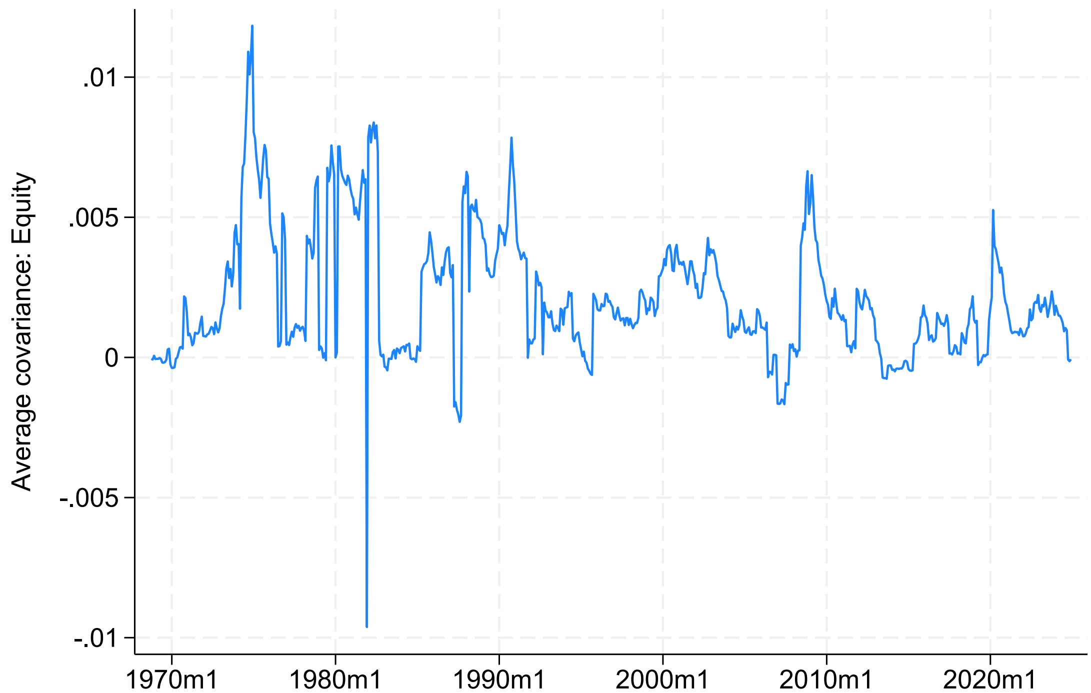

Figure 4. Average covariance in U.S. equities
The figure shows the average covariance between changes in realized and expected stock returns (equation (8)) in the CRSP firms' equity sample over the period 1968–2024.

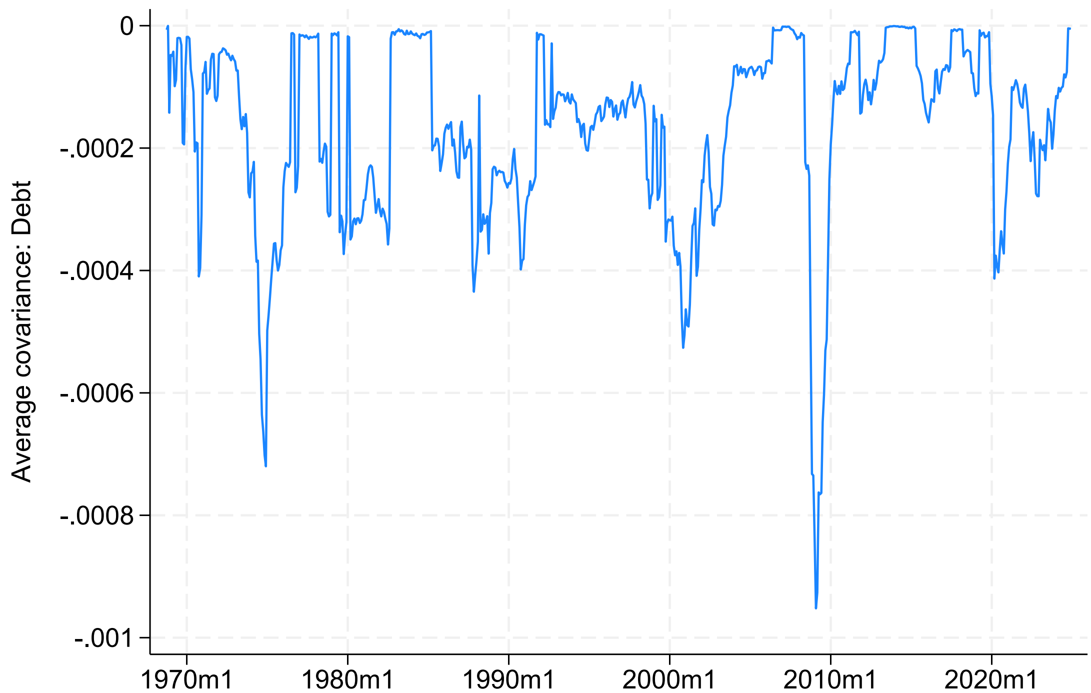

Figure 5. Average covariance in U.S. debt

The figure shows the average covariance between changes in realized and expected debt returns (equation (15)) in the CRSP firms' debt sample over the period 1968–2024.

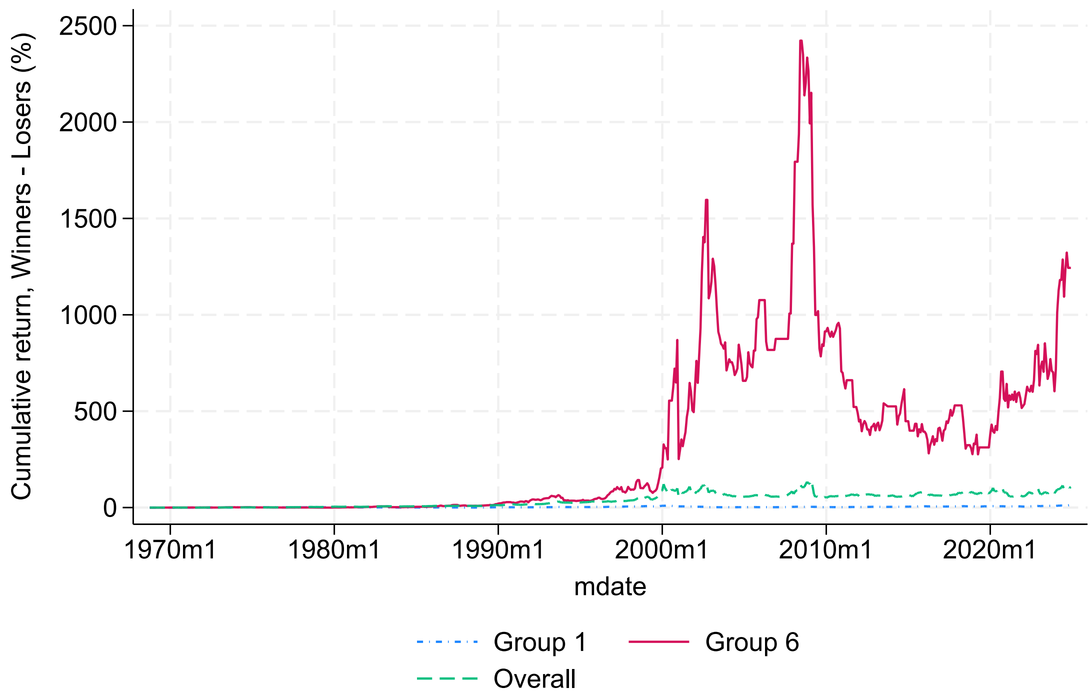

Figure 6. Cumulative return, Winners - Losers
The graphs plot cumulative returns on the value-weighted winners-minus-losers portfolios based on overall momentum, and Group 1 and Group 6 based on covariance of past stock returns and changes in expected returns. The CRSP firms' equity sample covers the period 1968–2024.

Table 1. Simulation results: Reduced-form momentum

The table reports monthly returns on the momentum strategy simulated in the model setting. We simulate daily realizations for assets A_t and variance V_t for 100,000 firms and five years, and price equity using Equation (1). We compute the corresponding monthly equity returns and sort the stocks into equally-weighted decile portfolios based on their return over the last 12 months and on $Cov_t > 0$, i.e., if the momentum condition is satisfied. The decile portfolios are held for one month. Win-Los denotes the difference between P10 (Winners) and P1 (Losers). We report mean, standard deviation, and several percentiles for the monthly holding period returns in %. We use the following annualized parameters: face value of debt uniformly distributed in the range $F = [10; 90]$, $\sigma_A = 0.1$, $\sigma_V = 0.2$, $\rho = -0.7$, $\kappa^{\mathbb{P}} = 3$, $\theta^{\mathbb{P}} = 0.05$, $\lambda_{IV} = -1.5$, fixed time-to-maturity $\tau = 3$, return on assets $\mu = 7\%$, and risk-free rate $r = 3\%$. All firms at the start are identical with assets $A_0 = 100$ and $V_0 = 0.07$.

Portfolio	Mean	Std	1^{st} Pct	25^{th} Pct	75^{th} Pct	99^{th} Pct
Losers	0.87	0.06	0.70	0.83	0.92	1.02
P2	1.03	0.08	0.85	0.96	1.10	1.18
P3	1.06	0.06	0.93	1.02	1.11	1.19
P4	1.08	0.07	0.89	1.03	1.12	1.23
P5	1.11	0.07	0.96	1.06	1.17	1.27
P6	1.15	0.07	1.02	1.11	1.20	1.33
P7	1.18	0.08	1.02	1.12	1.23	1.38
P8	1.21	0.08	1.07	1.15	1.27	1.39
P9	1.28	0.10	1.09	1.19	1.37	1.51
Winners	1.41	0.09	1.17	1.35	1.47	1.60
Win-Los	0.54	0.12	0.20	0.47	0.61	0.81

Table 2. Robustness tests for simulation
The table reports monthly returns on the momentum strategy simulated in the model setting. We simulate daily realizations for assets A_t and variance V_t for 100,000 firms and five years, and price equity using Equation (1).

	Panel A: Fixed Debt Level F			
	$F = 30$	$F = 50$	$F = 60$	$F = 80$
Losers	1.202	1.208	1.110	0.899
Winners	1.189	1.473	1.676	2.276
Win-Los	-0.012	0.264	0.566	1.377
	Panel B: Time-to-Maturity τ			
	$\tau = 1$	$\tau = 3$	$\tau = 7$	$\tau = 9$
Losers	2.239	1.357	0.962	0.880
Winners	2.757	2.044	1.677	1.586
Win-Los	0.518	0.687	0.715	0.706
	Panel C: Asset Risk Premium μ			
	$\mu = 0.05$	$\mu = 0.08$	$\mu = 0.14$	$\mu = 0.17$
Los	0.172	0.643	1.534	1.941
Winners	0.960	1.392	2.231	2.635
Win-Los	0.788	0.748	0.697	0.694
	Panel D: Implied Variance Risk Premium λ_V			
	$\lambda_V = -1$	$\lambda_V = -2$	$\lambda_V = -3$	$\lambda_V = -4$
Losers	1.086	1.094	1.101	1.105
Winners	1.857	1.807	1.785	1.769
Win-Los	0.771	0.713	0.684	0.665
	Panel E: Asset Volatility σ_A			
	$\sigma_A = 0.05$	$\sigma_A = 0.15$	$\sigma_A = 0.25$	$\sigma_A = 0.30$
Losers	0.814	0.634	0.493	0.661
Winners	1.197	1.314	1.700	2.062
Win-Los	0.383	0.680	1.206	1.401
	Panel F: Variance Volatility σ_V			
	$\sigma_V = 0.10$	$\sigma_V = 0.30$	$\sigma_V = 0.40$	$\sigma_V = 0.45$
Losers	0.823	0.781	0.924	0.964
Winners	1.152	1.255	1.408	1.465
Win-Los	0.329	0.473	0.484	0.501

Table 3. Momentum in U.S. equities

The table reports the holding period returns on portfolios sorted based on prior return deciles. Each calendar month t in the period 1968–2024 all CRSP common stocks are sorted into deciles based on their $t-12$ to $t-2$-month return, and a value-weighted decile portfolio return is computed for the period from time t to $t+1$ (skipping month $t-1$); we report the average raw returns and associated t-statistic on each of the decile portfolios, as well as the winners-minus-losers long-short portfolio. We split the sample into stocks that fail to satisfy the momentum condition (equation (9)) (Groups 1, 2, and 3) and stocks that satisfy the condition (Groups 4, 5, and 6). We reproduce the test for each group. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$.

	Overall	**Momentum condition**					
		Not satisfied			**Satisfied**		
		Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Losers	0.413	0.578	0.526	0.737	0.098	0.193	-0.077
	(1.93)	(2.31)	(1.90)	(2.26)	(0.22)	(0.39)	(-0.14)
2	0.727	0.767	0.863	0.691	0.282	0.066	0.352
	(3.40)	(3.35)	(3.80)	(2.51)	(0.66)	(0.15)	(0.78)
3	0.953	0.842	0.818	0.752	0.227	0.430	1.077
	(4.45)	(4.17)	(4.16)	(3.12)	(0.57)	(0.99)	(2.55)
4	0.886	0.933	0.984	0.804	0.257	0.652	0.927
	(4.14)	(4.93)	(5.35)	(3.69)	(0.68)	(1.78)	(2.43)
5	0.834	0.827	0.947	0.826	0.278	1.181	1.018
	(3.90)	(4.41)	(5.15)	(3.96)	(0.73)	(3.31)	(2.91)
6	0.963	0.827	0.978	0.974	0.276	0.688	1.280
	(4.50)	(4.67)	(5.09)	(4.78)	(0.85)	(2.04)	(3.73)
7	0.925	0.998	0.925	0.988	0.657	0.745	1.308
	(4.32)	(5.77)	(4.97)	(4.85)	(1.91)	(2.45)	(3.92)
8	1.096	0.771	1.091	0.970	0.792	0.906	1.576
	(5.11)	(4.19)	(6.05)	(4.43)	(2.37)	(2.87)	(4.81)
9	1.041	0.995	1.115	1.341	0.732	1.151	1.458
	(4.86)	(5.14)	(5.54)	(5.72)	(2.14)	(3.58)	(4.60)
Winners	1.395	1.070	1.311	1.581	1.611	1.555	1.305
	(6.52)	(5.00)	(5.75)	(5.34)	(3.82)	(3.94)	(3.52)
Win–Los	0.982	0.493	0.785	0.844	1.513	1.362	1.382
	(3.25)	(0.95)	(1.51)	(1.62)	(2.87)	(2.58)	(2.62)

Table 4. Momentum in U.S. equities: Risk-adjusted returns
The table reports the risk-adjusted holding period returns on portfolios sorted based on prior return deciles. Panel A shows the risk-adjusted returns based on the Fama and French (1993) 3-factor model and Panel B – based on the Fama and French (2016) 5-factor model. Each calendar month t in the period 1968–2024 all CRSP common stocks are sorted into deciles based on their $t-12$ to $t-2$-month return, and a value-weighted decile portfolio return is computed for the period from time t to $t+1$ (skipping month $t-1$); we report the average raw returns and associated t-statistic on each of the decile portfolios, as well as the winners-minus-losers long-short portfolio. We split the sample into stocks that fail to satisfy the momentum condition (equation (9)) (Groups 1, 2, and 3) and stocks that satisfy the condition (Groups 4, 5, and 6). We reproduce the test for each group. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$.

	Momentum condition					
	Not satisfied			**Satisfied**		
	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
	Panel A: Momentum portfolios – 3-Factor alphas					
Losers	-0.210	-0.301	0.050	-0.871	-0.896	-1.385
	(-1.37)	(-1.94)	(0.25)	(-2.64)	(-2.43)	(-3.26)
Winners	0.408	0.762	1.123	0.799	0.604	0.281
	(3.34)	(5.30)	(6.56)	(2.48)	(2.05)	(1.05)
Win–Los	0.618	1.063	1.073	1.670	1.500	1.666
	(1.67)	(2.87)	(2.90)	(4.45)	(3.99)	(4.43)
	Panel B: Momentum portfolios – 5-Factor alphas					
Losers	-0.318	-0.313	0.355	-0.627	-0.617	-0.884
	(-2.02)	(-1.97)	(1.78)	(-1.86)	(-1.64)	(-2.06)
Winners	0.268	0.660	1.249	0.901	0.687	0.299
	(2.17)	(4.51)	(7.19)	(2.75)	(2.27)	(1.09)
Win–Los	0.586	0.974	0.894	1.528	1.304	1.183
	(1.55)	(2.58)	(2.37)	(4.00)	(3.41)	(3.09)

Table 5. Momentum in U.S. equities, Fama-MacBeth regressions
The table reports the estimates of $r_{it+1} = \alpha + \beta\bar{r}_{it} \times \text{Cov}_{it} + \sum_k \gamma_k x_{kit} + \sum_k \delta_k \bar{r}_{it} \times x_{kit} + \varepsilon_{it}$, where r_{it+1} is the holding period return from time t until time $t+1$, $\bar{r}_{it}$ denotes Prior formation period return on stock i over the period from month $t-12$ to month $t-2$, (skipping month $t-1$), Cov_{it} is the covariance between past stock returns and changes in expected stock returns (equation (8)). In Column (2) we include various determinants of momentum $x_i t$: log-Market equity, log-Book-to-Market, Gross profits/Assets, log-Leverage (ratio of total book debt to total assets), log-share turnover ratio, log-Analyst coverage, log-Analyst forecast dispersion (standard deviation of analyst EPS forecasts divided by the mean estimate), credit rating indicator and their interactions with Prior formation period return, and Fama–French 30 industry indicators. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$. All regressions are estimated in the spirit of Fama and MacBeth (1973): one cross-sectional regression is estimated for each calendar month, and the table reports the average coefficient estimates; the t–statistics, reported in parentheses, are based on Newey–West standard errors with 12 lags.

Dependent variable: Return	(1)
Past return	-0.018
	(-1.68)
Covariance	0.921
	(0.40)
Past return × Covariance	0.201
	(1.96)
log-Market equity	-0.229
	(-6.46)
log-Book-to-Market	0.293
	(4.20)
Gross profits/Assets	0.507
	(3.30)
log-Leverage	0.110
	(1.45)
log-Turnover	-0.029
	(-0.53)
log-Analyst coverage	0.113
	(2.33)
log-Analyst forecast dispersion	-0.059
	(-1.83)
Credit rating	0.006
	(1.63)

Table continued on the next page

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	(1)
Interactions between Past return and:	
log-Market equity	0.002
	(2.66)
log-Book-to-Market	-0.003
	(-3.84)
Gross profits/Assets	-0.005
	(-2.03)
log-Leverage	0.003
	(2.62)
log-Turnover	-0.000
	(-0.02)
log-Analyst coverage	-0.001
	(-1.02)
log-Analyst forecast dispersion	0.002
	(3.98)
Credit rating	-0.000
	(-1.49)
Industry indicators	Y
Average R^2	0.169
N	876,651

Table 6. Momentum in U.S. corporate bonds

The table reports the raw holding period bond returns on portfolios sorted based on prior return deciles. CRSP common stocks are matched with their corresponding bonds from TRACE in the period 2002-2024. Column (1) shows the bond-level returns from time t to $t+1$ based on the bond-level past $t-12$ to $t-2$-month return. Column (2) shows the returns based on the firm-level bonds past $t-12$ to $t-2$-month return and Column (3) – based on the equity's past $t-12$ to $t-2$-month return (skipping month $t-1$). We report the equally-weighted average raw returns and associated t-statistic on each of the decile portfolios, as well as the winners-minus-losers long-short portfolio.

	Bond-level sort	**Firm-level sort**	**Equity sort**
	(1)	(2)	(3)
Losers	0.616	0.542	0.425
	(4.40)	(4.40)	(3.47)
2	0.334	0.335	0.377
	(2.33)	(2.65)	(3.08)
3	0.221	0.330	0.365
	(1.54)	(2.61)	(2.98)
4	0.214	0.234	0.360
	(1.50)	(1.85)	(2.94)
5	0.212	0.269	0.362
	(1.48)	(2.13)	(2.96)
6	0.221	0.275	0.353
	(1.54)	(2.18)	(2.89)
7	0.229	0.275	0.324
	(1.60)	(2.18)	(2.65)
8	0.246	0.300	0.352
	(1.72)	(2.38)	(2.88)
9	0.294	0.316	0.400
	(2.05)	(2.50)	(3.27)
Winners	0.390	0.422	0.440
	(2.72)	(3.34)	(3.59)
Win–Los	-0.227	-0.120	0.015
	(-1.13)	(-0.68)	(0.08)

Table 7. Momentum in U.S. corporate bonds: Equity-bond momentum spillover
The table reports the raw holding period bond returns on portfolios sorted based on prior return deciles. CRSP common stocks are matched with their corresponding bonds from TRACE in the period 2002-2024. Panel A shows the bond-level returns from time t to $t+1$ based on the bond-level past $t-12$ to $t-2$-month return. Panel B shows the returns from time t to $t+1$ of firm-level bonds sorted based on their own past $t-12$ to $t-2$-month return and Panel C – based on the equity's past $t-12$ to $t-2$-month return (skipping month $t-1$). We report the equally-weighted average raw returns and associated t-statistic on each of the decile portfolios, as well as the winners-minus-losers long-short portfolio. We split the sample into stocks that fail to satisfy the momentum condition (equation (9)) (Groups 1, 2, and 3) and stocks that satisfy the condition (Groups 4, 5, and 6). We reproduce the test for each group. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$.

	Equity momentum condition					
	Not satisfied			**Satisfied**		
	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
	Panel A: Bond momentum portfolios – bond-level sorts					
Losers	0.182	0.375	0.914	0.687	0.595	0.471
	(0.12)	(0.11)	(0.22)	(0.22)	(0.21)	(0.26)
Winners	0.331	0.294	0.253	0.277	0.673	0.281
	(0.13)	(0.12)	(0.22)	(0.26)	(0.23)	(0.27)
Win–Los	0.149	-0.081	-0.661	-0.410	0.078	-0.190
	(0.85)	(-0.50)	(-2.12)	(-1.21)	(0.25)	(-0.51)
	Panel B: Bond momentum portfolios – firm-level sorts					
Losers	0.294	0.387	0.857	0.626	0.323	-0.076
	(0.11)	(0.11)	(0.21)	(0.26)	(0.24)	(0.33)
Winners	0.347	0.328	0.339	0.515	0.896	0.624
	(0.12)	(0.11)	(0.22)	(0.40)	(0.32)	(0.40)
Win–Los	0.053	-0.059	-0.518	-0.111	0.573	0.700
	(0.33)	(-0.37)	(-1.67)	(-0.23)	(1.45)	(1.36)
	Panel C: Bond momentum portfolios – equity sorts					
Losers	0.149	0.369	0.218	0.528	0.468	0.227
	(0.12)	(0.13)	(0.16)	(0.24)	(0.22)	(0.24)
Winners	0.353	0.343	0.342	0.599	1.342	1.068
	(0.11)	(0.12)	(0.15)	(0.27)	(0.28)	(0.31)
Win–Los	0.204	-0.026	0.124	0.071	0.874	0.841
	(1.23)	(-0.15)	(0.57)	(0.19)	(2.46)	(2.13)

Table 8. Momentum crashes in U.S. equities

The table reports predictive regressions using the one-month lagged fraction of stock satisfying the momentum condition as an explanatory variable. In Panel A the dependent variable is an indicator for overall momentum crashes in the CRSP 1968-2024 sample of common stocks (in Columns (1) and (2)), while in Columns (3) and (4) the momentum crashes are among winner-loser portfolios constructed using on stocks in Group 6 based on the covariance between changes in past and expected equity returns. In Columns (1) and (3) the momentum crashes indicator takes the value of 1 when the winners-loser portfolio returns are below the 5th bottom percentile of the distribution, and 0 otherwise. In Column (2) and (4) the momentum crash indicator takes the value of 1 when the winners-loser portfolio returns are below the 10th bottom percentile of the distribution, and 0 otherwise. In Panel B the dependent variable is the top losers (indicator for loser returns above the top 5th percentile (in Columns (1) and (3) and above the top 10th percentile in Columns (2) and (4)). In Panel C the dependent variable is the bottom losers (indicator for winner returns below the bottom 5th percentile (in Columns (1) and (3) and below the bottom 10th percentile in Columns (2) and (4)). The table reports the coefficient estimates and the t-statistics based on robust standard errors reported in brackets below.

	Overall		**Group 6**	
	(1)	**(2)**	**(3)**	**(4)**
	Panel A: Dep. variable Momentum crash			
Fraction satisfying	0.470	0.551	0.209	0.370
momentum condition	(4.19)	(4.14)	(2.11)	(2.89)
Average R^2	0.056	0.036	0.036	0.014
N	674	674	674	674
	Panel B: Dep. variable Top losers			
Fraction satisfying	0.258	0.459	0.084	0.153
momentum condition	(2.00)	(3.15)	(0.69)	(1.13)
Average R^2	0.011	0.022	0.001	0.003
N	674	674	674	674
	Panel C: Dep. variable Bottom winners			
Fraction satisfying	0.205	0.238	0.018	-0.064
momentum condition	(2.23)	(2.19)	(0.21)	(-0.58)
Average R^2	0.001	0.009	0.000	0.001
N	674	674	674	674

Online Appendix

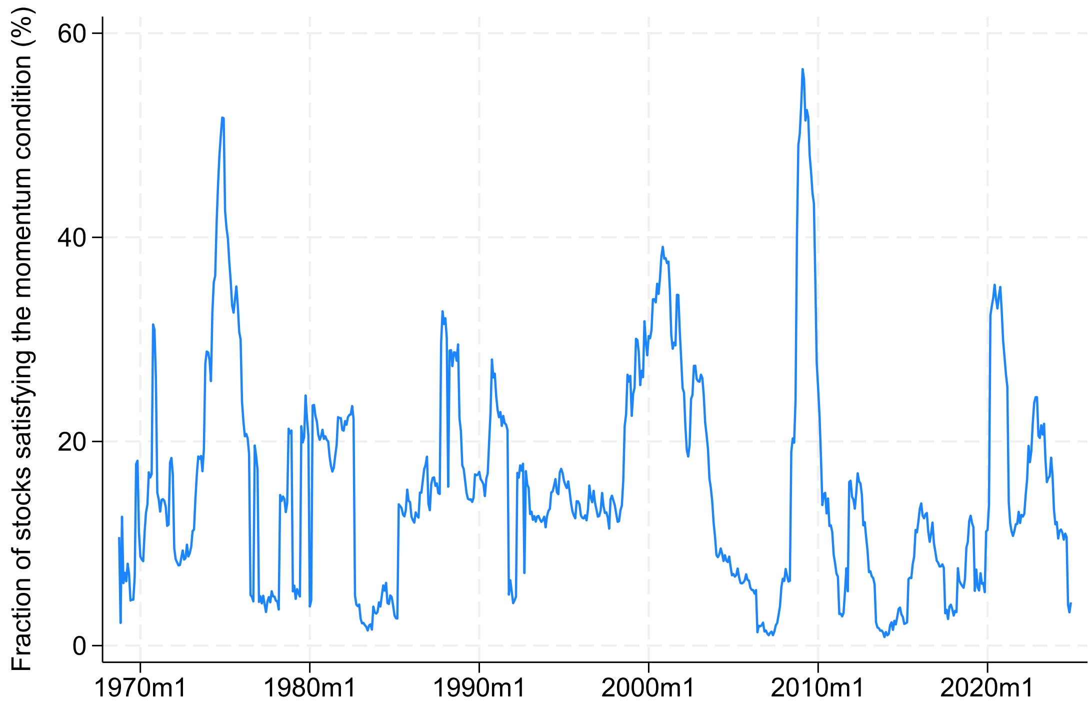

Figure A.1. Percentage of U.S. equities satisfying the momentum condition
The figure shows the ratio of the number of stocks satisfying the momentum condition (equation (9)) to the number of stocks in the CRSP database over the period 1968–2024.

Table A.1. Simulation results: Merton Model

The table reports monthly returns on the momentum strategy simulated in the Merton (1974) model. We simulate daily realizations for assets A_t for 100,000 firms and five years, and price equity using the Black-Scholes-Merton formula. We compute the corresponding monthly equity returns and sort the stocks into equally-weighted decile portfolios based on their return over the last 12 months. The decile portfolios are held for one month. Win-Los denotes the difference between P10 (Winners) and P1 (Losers). We report mean, standard deviation, and several percentiles for the monthly holding period returns in %. We use the following annualized parameters: face value of debt uniformly distributed in the range $F = [10; 90]$, $\sigma_A = 0.25$, fixed time-to-maturity $\tau = 3$, return on assets $\mu = 7\%$, and risk-free rate $r = 3\%$. All firms at the start are identical with assets $A_0 = 100$.

Portfolio	Mean	Std	1^{st} Pct	25^{th} Pct	75^{th} Pct	99^{th} Pct
Losers	3.11	0.36	2.31	2.84	3.37	3.76
P2	1.58	0.13	1.30	1.51	1.64	1.93
P3	1.22	0.14	0.88	1.13	1.32	1.50
P4	1.15	0.14	0.94	1.04	1.26	1.49
P5	1.10	0.11	0.90	1.02	1.18	1.41
P6	1.08	0.13	0.77	0.99	1.17	1.33
P7	1.03	0.11	0.75	0.95	1.09	1.26
P8	1.06	0.13	0.70	0.97	1.14	1.40
P9	1.07	0.15	0.72	0.96	1.15	1.46
Winners	1.30	0.22	0.92	1.14	1.52	1.77
Win − Los	-1.81	0.30	-2.51	-1.99	-1.64	-1.13

Table A.2. Momentum in U.S. equities: Independent sorts
The table reports the holding period returns on portfolios sorted based on prior return deciles. Each calendar month t in the period 1968–2024 all CRSP common stocks are sorted into deciles based on their $t-12$ to $t-2$-month return, and a value-weighted decile portfolio return is computed for the period from time t to $t+1$ (skipping month $t-1$); we report the average raw returns and associated t-statistic on each of the decile portfolios, as well as the winners-minus-losers long-short portfolio. We split the sample into stocks that fail to satisfy the momentum condition (equation (9)) (Groups 1, 2, and 3) and stocks that satisfy the condition (Groups 4, 5, and 6). We form the portfolios according to the independent sorts based on past returns and the six groups. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$.

	Overall	**Momentum condition**					
		Not satisfied			**Satisfied**		
		Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Losers	0.413	0.536	0.571	0.605	-0.028	0.110	-0.127
	(1.93)	(1.87)	(1.82)	(1.78)	(-0.07)	(0.26)	(-0.28)
2	0.727	0.888	0.727	0.724	0.169	0.472	0.827
	(3.40)	(3.72)	(2.82)	(2.48)	(0.44)	(1.27)	(2.12)
3	0.953	0.957	1.084	0.850	0.202	0.805	0.768
	(4.45)	(4.32)	(4.91)	(3.51)	(0.57)	(2.21)	(2.09)
4	0.886	0.908	0.842	0.900	0.235	0.896	1.243
	(4.14)	(4.62)	(4.35)	(3.98)	(0.67)	(2.53)	(3.82)
5	0.834	0.831	0.994	0.687	0.863	0.368	1.376
	(3.90)	(4.29)	(5.16)	(3.17)	(2.49)	(1.13)	(4.02)
6	0.963	0.836	1.026	0.920	0.909	1.093	1.485
	(4.50)	(4.53)	(5.46)	(4.64)	(2.61)	(3.33)	(4.28)
7	0.925	0.986	0.918	0.976	0.531	1.087	1.511
	(4.32)	(5.39)	(4.98)	(4.86)	(1.45)	(3.18)	(4.23)
8	1.096	1.044	1.115	1.128	0.927	1.385	1.093
	(5.11)	(5.40)	(5.99)	(5.50)	(2.61)	(3.85)	(3.08)
9	1.041	0.937	1.075	1.051	1.019	1.301	1.450
	(4.86)	(4.52)	(5.49)	(4.90)	(2.78)	(3.20)	(3.92)
Winners	1.395	1.136	1.335	1.448	1.823	1.578	2.161
	(6.52)	(4.74)	(5.71)	(5.50)	(4.11)	(3.58)	(4.17)
Win–Los	0.982	0.600	0.764	0.842	1.851	1.468	2.288
	(3.25)	(1.17)	(1.50)	(1.66)	(3.52)	(2.80)	(4.24)

Table A.4. Momentum in U.S. equities: Debt maturity 3 years
The table reports the holding period returns on portfolios sorted based on prior return deciles. In this table we use debt maturity of three years. Each calendar month t in the period 1968–2024 all CRSP common stocks are sorted into deciles based on their $t-12$ to $t-2$-month return, and a value-weighted decile portfolio return is computed for the period from time t to $t+1$ (skipping month $t-1$); we report the average raw returns and associated t-statistic on each of the decile portfolios, as well as the winners-minus-losers long-short portfolio. We split the sample into stocks that fail to satisfy the momentum condition (equation (9)) (Groups 1, 2, and 3) and stocks that satisfy the condition (Groups 4, 5, and 6). We reproduce the test for each group. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and correlation between the assets and implied variance processes $\rho = -0.7$.

	Overall	**Momentum condition**					
		Not satisfied			**Satisfied**		
		Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Losers	0.476	0.803	0.850	0.908	0.666	0.389	0.078
	(2.20)	(2.94)	(3.36)	(2.72)	(1.86)	(1.02)	(0.21)
2	0.796	1.225	0.827	0.458	0.747	0.522	0.354
	(3.68)	(5.59)	(3.85)	(1.60)	(2.48)	(1.69)	(1.05)
3	1.020	1.097	0.843	1.022	0.814	0.746	0.758
	(4.71)	(5.81)	(4.35)	(3.81)	(3.09)	(2.67)	(2.62)
4	0.940	0.819	0.905	0.957	0.684	0.531	0.623
	(4.34)	(4.77)	(4.68)	(3.84)	(2.74)	(2.03)	(2.24)
5	0.875	0.946	1.006	0.863	0.824	0.831	0.846
	(4.04)	(5.46)	(5.22)	(3.72)	(3.53)	(3.37)	(3.11)
6	1.025	0.820	1.012	0.994	0.693	0.779	0.876
	(4.74)	(4.90)	(5.13)	(4.35)	(2.89)	(3.30)	(3.47)
7	0.987	0.872	1.127	1.050	0.987	0.906	1.111
	(4.55)	(5.21)	(5.82)	(4.62)	(4.20)	(3.85)	(4.53)
8	1.143	1.018	1.125	1.102	1.143	1.055	1.203
	(5.27)	(5.90)	(5.50)	(4.65)	(4.70)	(4.53)	(4.87)
9	1.092	1.193	1.095	1.273	1.105	1.051	1.099
	(5.04)	(6.71)	(5.31)	(4.81)	(4.33)	(4.27)	(4.43)
Winners	1.443	1.132	1.426	1.647	1.226	1.452	1.206
	(6.67)	(5.78)	(6.23)	(5.32)	(3.82)	(5.10)	(4.38)
Win–Los	0.967	0.329	0.577	0.739	0.560	1.063	1.129
	(3.16)	(0.76)	(1.34)	(1.71)	(1.30)	(2.47)	(2.62)