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 variance effects, producing momentum when the variance channel dominates and forecasting momentum crashes when the leverage channel prevails. 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, credit risk, 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, or the tendency of past winners to outperform past losers in securities markets, remains one of the most enduring and pervasive patterns in securities returns. Despite a voluminous academic literature and its widespread adoption in practice as a core ingredient of quantitative strategies and technical trading rules, momentum remains difficult to reconcile with standard risk-based asset pricing models.[1] Existing explanations often appeal to learning, behavioral frictions, or limits to arbitrage, leaving open a more fundamental question: can momentum arise endogenously from standard corporate finance primitives, i.e., from the interaction of firm fundamentals, leverage, and risk, in a fully rational setting?

We propose a novel, parsimonious explanation for momentum that matches key stylized facts documented in the empirical literature and addresses several outstanding challenges. We argue that momentum can arise naturally from the nonlinear mapping between firm asset values and equity returns implied by standard structural models of credit risk (Merton, 1974). Because equity is a levered residual claim, past equity returns mechanically affect leverage and, in turn, the sensitivity of equity to shocks in firm fundamentals. This generates two opposing forces. On the one hand, poor past returns increase leverage, raising equity's exposure to asset-level shocks and thereby increasing expected returns—the *leverage channel*. On the other hand, for a given level of asset volatility, higher leverage increases the option value of equity, raising prices today and lowering expected returns—the

[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.

variance channel. Whether momentum emerges depends on which force dominates: when the variance channel outweighs the leverage channel, past losers exhibit lower expected returns than past winners, generating return continuation.

We formalize this mechanism in a structural model of equity returns based on the Merton (1974) framework, augmented with implied stochastic volatility (Aït-Sahalia, Li, and Li, 2020; Carr and Wu, 2020). Implied stochastic volatility serves as a reduced-form pricing state variable that captures risks that cannot be dynamically spanned by the underlying asset (such as stochastic volatility and jumps), while preserving analytical tractability. The model delivers a closed-form condition that characterizes which firms are expected to drive momentum. In simulated data, the model generates momentum profits of a magnitude comparable to those documented in the literature; in real data on U.S. equities and corporate bonds, we find strong empirical support for the model's predictions. Importantly, momentum in our framework arises under rational expectations and frictionless trading, and reflects the endogenous interaction between capital structure and priced risk, rather than behavioral biases or limits to arbitrage.

We articulate our analysis in three parts. First, we develop the theoretical mechanism and derive a necessary condition for momentum within a Merton (1974) framework augmented with implied stochastic volatility. The condition links the sensitivity of equity value to changes in firm asset value (the leverage channel) and to changes in implied volatility (the variance channel) to the corresponding risk premia. Momentum arises when the variance channel dominates the leverage channel, so that past losers have lower expected returns than past winners. Despite its simplicity, the framework is flexible and yields a range of testable implications. For example, it delivers an analogous condition for momentum in corporate debt. The same logic also yields a structural explanation for momentum crashes. When systematic shocks dominate winner and loser portfolio returns, the strategy's exposure to aggregate risk is state dependent and forecastable. In these episodes, a positive aggregate shock to firm asset values disproportionately benefits highly levered firms (i.e., the leverage channel dominates), causing loser returns to exceed winner returns and producing sharp reversals in momentum profits.

Second, we assess the quantitative implications of the model through simulations based on the Merton framework augmented with implied stochastic volatility. Under realistic parameter values, the model generates momentum returns of a magnitude comparable to those documented in the empirical literature. For example, Jegadeesh and Titman (1993) and Daniel and Moskowitz (2016) report momentum profits of roughly 60–100 basis points per month (7.2%-12% in annual terms). In simulations with otherwise identical firms that differ only in leverage, we obtain momentum returns of similar economic magnitude, at 6.6% in annual terms.

The simulations also replicate several well-known cross-sectional patterns in the data. Consistent with Zhang (2006), momentum is stronger among firms with higher asset volatility, with simulated returns increasing monotonically as variance rises. Likewise, in line with Avramov, Chordia, Jostova, and Philipov (2007), momentum is concentrated among firms with higher credit risk: in the model, momentum emerges only when a subset of firms operates at sufficiently high leverage. Taken together, the simulation evidence shows that the structural mechanism not only generates momentum in theory, but does so in a way that quantitatively matches key empirical regularities.

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 118 to 166 bps per month (17 - 19% in annualized terms), depending on the risk adjustment. Among stocks that do not satisfy the condition, winners-minus-losers returns are smaller and not significantly different from zero. 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 two 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, Feldhütter, Pedersen, and Stolborg (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 also 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, Feldhütter, Pedersen, and Stolborg, 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, consistent with our model predictions, momentum crash risk is strongly forecast in periods of high predicted momentum returns and widespread satisfaction of the momentum condition, as leverage asymmetries and systematic exposure become elevated. As a result, large market rebounds occurring in these states generate severe losses. This predictability is driven primarily by the leverage channel, as crashes occur when the strategy becomes negatively exposed to aggregate asset shocks due to rising leverage among loser stocks. These findings are consistent with Daniel and Moskowitz (2016).

Relation to the literature. Our paper makes three main contributions. First, it contributes to the extensive literature on momentum by providing a simple, structural explanation grounded in corporate finance primitives. Following the seminal

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

study of Jegadeesh and Titman (1993), momentum has been documented across international equity markets (e.g., Rouwenhorst, 1998), corporate bonds (Jostova, Nikolova, Philipov, and Stahel, 2013), and asset classes such as commodities and indexes (Asness, Moskowitz, and Pedersen, 2013). Alongside this evidence, a large literature has proposed rational and behavioral explanations for momentum (see Jegadeesh and Titman (2011) for a review). Within the class of rational models, Sagi and Seasholes (2007) and Garlappi and Yan (2011) show that convexity arising from risky growth options or shareholders' recovery value can generate autocorrelation in equity returns and momentum, often relying on mean reversion in fundamentals or effectively unlevered firms. By contrast, our framework shows how implied stochastic volatility can generate convexity and momentum in a setting with leverage and without assuming mean reversion. Equity is a levered call on firm assets, and shocks to implied volatility increase the dispersion of future asset values; because limited liability protects shareholders on the downside, such shocks affect expected returns. Our contribution is to derive a closed-form condition under which this variance-driven convexity dominates the leverage effect, generating momentum while simultaneously constraining the joint behavior of equity and debt, and unifying momentum patterns across asset classes within a single, tractable model.

Second, and more broadly, our paper relates to the asset pricing literature on the cross-section of stock returns (Fama and French, 1993, 2012, 2016, 2017; Griffin, 2002; Hou, Andrew, and Kho, 2011). While recent work has questioned the robustness of many documented anomalies and advocated more conservative statistical standards (Harvey, Liu, and Zhu, 2016; Hou, Xue, and Zhang, 2020; Linnainmaa and Roberts, 2018), momentum is widely viewed as one of the most robust return patterns. Our results suggest that momentum need not be interpreted as an anomaly: it can arise in a fully rational, arbitrage-free setting once equity's nonlinear exposure to firm fundamentals and priced volatility risk is taken into account.

Third, our paper contributes to the literature on structural models of credit risk initiated by Merton (1974) and developed in Black and Cox (1976); Friewald, Wagner, and Zechner (2014); Leland (1994); Leland and Toft (1996); Longstaff and Schwartz (1995); Schaefer and Strebulaev (2008). While more recent studies incorporate additional risk sources such as jumps or stochastic volatility (Bandi, Fusari, and Renò, 2023; Collin-Dufresne, Junge, and Trolle, 2024; Du, Elkamhi, and Ericsson, 2019; Zhang, Zhou, and Zhu, 2009), we instead draw on advances from the equity option literature that use implied volatility as a sufficient statistic summarizing risks beyond the Black-Scholes-Merton framework (Aït-Sahalia, Li, and Li, 2020; Carr and Wu, 2020). This approach allows us to link structural credit risk directly to momentum in equity and bond markets.

2 Structural model

2.1 Framework

We build on the Merton (1974) model, in which 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. 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

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

the underlying, making the market incomplete. Such risks 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, Elkamhi, and Ericsson, 2019; Zhang, Zhou, and Zhu, 2009).

Extending models to include sources of market incompleteness often comes at the cost of analytical tractability and fails 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 requiring a full specification of asset dynamics. We leverage their framework and use the Black–Scholes–Merton (BSM) pricing formula to price equity $E(t, A(t), F, V(t, F), T)$ as a call option on total assets $A(t)$ with implied variance $V(t, F)$. While Carr and Wu (2020) do not study momentum, we use their framework as a tractable valuation device to analyze how option-like equity payoffs and time variation in implied variance generate momentum.

Each firm issues a single class of debt, a zero-coupon bond with face value F such that

$$E = A\,\Phi\left(\frac{\log\left(\frac{A}{Fe^{-\tau r_f}}\right) + \frac{V}{2}\tau}{\sqrt{V\,\tau}}\right) - Fe^{-\tau r_f}\,\Phi\left(\frac{\log\left(\frac{A}{Fe^{-\tau r_f}}\right) - \frac{V}{2}\tau}{\sqrt{V\,\tau}}\right), \tag{1}$$

where we suppress the arguments of E, A, and V whenever they are obvious and define time-to-maturity $\tau = T - t$ and the risk-free rate as r_f. The approach interprets the implied variance $V(t, F)$ as a summary statistic that captures all pricing-relevant risks. 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 variance at the center of the valuation process in a manner analogous to Aït-Sahalia, Li, and Li (2020). This approach preserves closed-form pricing expressions, simplifies empirical implementation as it only requires estimates of implied variance, and allows for flexibility in specifying the dynamics of implied variance to mimic known structural models.

The central idea of Carr and Wu (2020) is that the instantaneous change in a call option (equity E in our context) can be approximated via a second-order Taylor expansion:

$$\begin{aligned} dE = -E_\tau dt + E_A\, dA + E_V dV + \frac{1}{2} E_{AA}\,(dA)^2 \\ + \frac{1}{2} E_{VV}\,(dV)^2 + E_{AV}\, dA\, dV + \text{Asset Jumps}, \end{aligned} \tag{2}$$

where we use $E_\tau, E_A, E_V, E_{AA}, E_{VV}$, and E_{AV} to denote partial derivatives of equity with respect to time-to-maturity τ, total assets A, and implied variance V. The 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):

$$\begin{aligned} E_A(\mu(t) - r_f(t)) + E_V(\mu_V^{\mathbb{P}}(t) - \mu_V^{\mathbb{Q}}(t)) + \frac{1}{2} E_{AA}(\sigma_A^{2,\mathbb{P}}(t) - \sigma_A^{2,\mathbb{Q}}(t)) \\ + \frac{1}{2} E_{VV}(\sigma_V^{2,\mathbb{P}}(t) - \sigma_V^{2,\mathbb{Q}}(t)) + E_{AV}(\rho^{\mathbb{P}}(t) - \rho^{\mathbb{Q}}(t)) + JP(t), \end{aligned} \tag{3}$$

where $\mu(t)$ and $\sigma_A(t)$ denote the (potentially) time-varying drift and volatility of

[4] Note that the sensitivities with respect to V have to be expressed in terms of variance, not volatility.

total assets, $\mu_V(t)$ and $\sigma_V(t)$ are the drift and volatility of implied variance, $\rho(t)$ 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 modeling 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. Finally, the particular specifications of the dynamics of the state variables A and V 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:

$$\begin{aligned} \frac{dA}{A} &= \mu\, dt + \sigma_A\, dW^{A,\mathbb{P}} \\ dV &= \kappa(\theta - V)\, dt + \sigma_V \sqrt{V}\, dW^{V,\mathbb{P}}, \end{aligned} \tag{4}$$

[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.

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

$$\begin{aligned} \frac{dA}{A} &= r_f\,dt + \sigma_A\,dW^{A,\mathbb{Q}} \\ dV &= \kappa^{\mathbb{Q}}(\theta^{\mathbb{Q}} - V)\,dt + \sigma_V\sqrt{V}\,dW^{V,\mathbb{Q}}, \end{aligned} \tag{5}$$

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 implied variance 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 (Bandi, Fusari, and Renò, 2023; Du, Elkamhi, and Ericsson, 2019, e.g.,). In our setup $V(t)$ is not the time-varying asset variance (the variance of assets is described with σ_A^2) but rather captures compensation for all sources of market incompleteness. For ease of interpretation however, we assume this to be stochastic asset variance.[6]

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

$$\mathbb{E}_t^{\mathbb{P}}[dE] - \mathbb{E}_t^{\mathbb{Q}}[dE] = (E_A A(\mu - r_f) + E_V V \lambda_V)\,dt, \tag{6}$$

where $\mathbb{E}_t$ is the conditional expectation at time t. Hence, the expected change in

[6] Alternatively, the source of incompleteness could be asset jumps or higher moments for instance. 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 and prices of risk also impacts assets. For instance, a discount rate shock would increase $V(t)$ as $dW_t^V > 0$. With $\rho < 0$, the higher discount rate decreases the value of assets.

equity consists of a leverage premium term $E_A A(\mu - r_f)$ and a variance premium term $E_V V \lambda_V$. Substituting $\mathbb{E}_t^{\mathbb{Q}}[dE] = r_f E\, dt$ and dividing (6) by E, we get the expected simple equity return:

$$g(t) = \frac{\mathbb{E}_t^{\mathbb{P}}[dE]/E}{dt} = r_f + \eta^A(\mu - r_f) + \eta^V \lambda_V, \tag{7}$$

where $\eta^A = E_A \frac{A}{E}$ and $\eta^V = E_V \frac{V}{E}$ elasticity of the value of equity to 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.

Formally, the change in expected returns is given by:

$$dg = g_A \sigma_A A\, dW^A + g_V \sigma_V \sqrt{V}\, dW^V + O(dt), \tag{8}$$

where

$$g_A = \frac{\partial \eta^A}{\partial A}(\mu - r_f) + \frac{\partial \eta^V}{\partial A}\lambda_V, \qquad g_V = \frac{\partial \eta^A}{\partial V}(\mu - r_f) + \frac{\partial \eta^V}{\partial V}\lambda_V.$$

The term $O(dt)$ is the drift that collects all dt terms. The realized return is given by

$$r(t) = \frac{1}{E}\Big(E_A \sigma_A A\, dW_t^A + E_V \sigma_V \sqrt{V}\, dW_t^V + O(dt)\Big). \tag{9}$$

At order dt, only the martingale components covary. Therefore,

$$\frac{\mathrm{Cov}_t(dg, r)}{dt} = \frac{1}{E}\left(g_A E_A \sigma_A^2 A^2 + g_V E_V \sigma_V^2 V + \rho \sigma_A \sigma_V A \sqrt{V}(g_A E_V + g_V E_A)\right), \tag{10}$$

because $(dt)^2 = 0$, $(dt\, dW) = 0$, $(dW)^2 = dt$, and $(dW^A dW^V) = \rho\, dt$. Thus, the condition for momentum is that:

$$\mathrm{Cov}_t\,(dg, r) > 0. \tag{11}$$

Appendix A gives analytical expressions for $\frac{\partial\eta^A}{\partial A}$, $\frac{\partial\eta^V}{\partial A}$, $\frac{\partial\eta^A}{\partial V}$, and shows that the partial derivatives are strictly negative. $\frac{\partial\eta^V}{\partial V}$ 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 $(\mu - r_f)$ is positive, the contribution of $\frac{\partial\eta^A}{\partial A}$ and $\frac{\partial\eta^A}{\partial V}$ on expected returns is generally negative (leverage channel). As $\lambda_V < 0$, meaning that investors are willing to pay to hedge against risks such as stochastic variance, the contribution of $\frac{\partial\eta^V}{\partial A}$ is positive (variance channel).[7] The effect of $\frac{\partial\eta^V}{\partial V}$ is ambiguous and depends on the leverage and variance of the firm.

We analyze $\mathrm{Cov}_t(dg, r)$ as a function of leverage (F/A) and variance V 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 variance effect for low-levered and low-variance firms. The variance channel dominates for high risk firms (high leverage and/or high variance).

Simulating the model

As a second step in our analysis, we simulate the model to assess if it is capable of producing momentum returns of similar magnitude to those documented in the literature. We model 100,000 firms that have identical total assets A of 100 and

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

implied variance V of 7% at the start $t = 0$. 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 $\mu - r_f$ is 4% and the price of implied variance risk λ_V is -1.5 (Zhang, Zhou, and Zhu, 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 $\sigma_A = 0.10$, $\sigma_V = 0.20$, $\rho = -0.7$, $\kappa = 3$, $\theta = 0.05$, which are in-line with estimates from Bandi, Fusari, and Renò (2023), Du, Elkamhi, and Ericsson (2019), and Collin-Dufresne, Junge, and Trolle (2024).

To test the model, we implement a similar strategy as in the empirical momentum literature. We first simulate five years of daily paths of the state variables A and V and price equity with Equation (1). Next, we aggregate the realizations to monthly frequency and sort firms (i) based on whether $\text{Cov}_t\,(dg, r) > 0$ and (ii) into deciles based on their past 12 month equity returns. 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 $\text{Cov}_t(dg, r) > 0$). 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.[8]

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, Chordia, Jostova, and Philipov (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 variance 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 $(\mu - r_f)$ (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% per month.

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:

$$D = A - E. \tag{12}$$

Because corporate debt is the residual between assets and equity, it follows read-

[8] In Appendix Table A.1, we repeat the simulations using the Merton (1974) model and show that the variance channel is indeed necessary to generate momentum as the spread between the winner and loser portfolio is strongly negative.

ily that the expected return for debt is given by:

$$g^D = \frac{\mathbb{E}_t^{\mathbb{P}}[dD]/D}{dt} = r_f + \zeta^A(\mu - r_f) + \zeta^V \lambda_V \tag{13}$$

with the bond's elasticity to total assets $\zeta^A = \frac{D_A A}{D}$ and implied variance $\zeta^V = \frac{D_V V}{D}$. The variables D_A and D_V are partial derivatives of the bond value with respect to total assets and variance.

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

$$r^D = \frac{1}{D}\big(D_A dA + D_V dV\big) + O(dt),$$

and the change in expected bond returns is given by:

$$dg^D = g_A^D dA + g_V^D dV + O(dt), \tag{14}$$

with:

$$\begin{aligned} g_A^D &= \tfrac{\partial \zeta^A}{\partial A}(\mu - r_f) + \tfrac{\partial \zeta^V}{\partial A}\lambda_V \\ g_V^D &= \tfrac{\partial \zeta^A}{\partial V}(\mu - r_f) + \tfrac{\partial \zeta^V}{\partial V}\lambda_V. \end{aligned} \tag{15}$$

The conditional covariance is:

$$\frac{\mathrm{Cov}_t(dg^D, r^D)}{dt} = \frac{1}{D}\Big[g_A^D D_A \sigma_A^2 A^2 + g_V^D D_V \sigma_V^2 V + \rho\sigma_A\sigma_V A\sqrt{V}\big(g_A^D D_V + g_V^D D_A\big)\Big]. \tag{16}$$

Hence, we expect momentum in bonds when:

$$\mathrm{Cov}_t(dg^D, r^D) > 0. \tag{17}$$

As Equation (12) 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 $\mathrm{Cov}_t(dg^D, r^D)$ 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 is not 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 and 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 regardless 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.

Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2025) find that equity momentum can predict bond returns, i.e., momentum spillover. In our model, this translates to a positive association between expected bond returns and realized equity returns. That is:

$$\frac{\mathrm{Cov}_t(dg^D, r)}{dt} = \frac{1}{E}\Big[g_A^D E_A \sigma_A^2 A^2 + g_V^D E_V \sigma_V^2 V + \rho\sigma\sigma_V A\sqrt{V}\big(g_A^D E_V + g_V^D E_A\big)\Big]. \quad (18)$$

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 predictability of past equity returns for future bond returns.

3 Empirical evidence

In this section, we test the predictions of the model developed in Section 2 using empirical data. The model delivers two central implications. First, momentum should arise only among stocks that satisfy the momentum condition in equation (11). Second, conditional on satisfying this condition, the magnitude of momentum should increase with the covariance between realized stock returns and innovations in expected returns. We evaluate these predictions in U.S. equities and assess their robustness by controlling for a range of variables commonly associated with momentum in Fama–MacBeth regressions.

3.1 Momentum in U.S. equities

We obtain monthly returns for common stocks (CRSP share codes 10 and 11) listed on the NYSE, Amex, and NASDAQ from CRSP, and merge them with accounting data from Compustat over the period 1968–2024. Following Daniel and Moskowitz (2016), we require firms to have at least eight non-missing monthly returns over the past 11 months, skipping the most recent month, which serves as the formation period for the momentum strategy. To attenuate the influence of penny stocks and microcaps, we exclude stocks with prices below \$1 (Jegadeesh and Titman, 2001) and firms in the bottom decile of NYSE market capitalization (Fama and French, 2008). To mitigate the effect of outliers, monthly stock returns are winsorized at the 0.5^{th} and 99.5^{th} percentiles.

To construct an empirical counterpart to the momentum condition in equation (11), we estimate firm-level inputs from the structural model in Section 2 using equity returns and balance sheet debt data, following the approach of Bharath and Shumway (2008). Specifically, historical equity returns are used to estimate the required return on total assets, μ. The procedure begins with an initial estimate of implied volatility, $\sqrt{V(t)} = \sigma_E(t)\,\frac{E}{E+F}$, which is then used to infer the market value of assets, $A(t)$, from the pricing equation (1).[9] This mapping yields an implied time series of realized asset returns over the previous year from which updated estimates of $\sqrt{V(t)}$ is obtained. The updated volatility estimate is then fed back into the pricing equation to re-estimate $A(t)$, and the procedure is iterated until convergence.

Consistent with our model, we fix the following parameters when evaluating the momentum condition: an asset risk premium of $\mu - r_f = 4\%$, a variance risk premium of $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_{IV} = 0.20$, and a correlation of $\rho = -0.7$ between asset and implied variance shocks. These estimates allow us to partition the CRSP universe each month into firms that satisfy

[9] Note that $\sigma_E(t)$ is the volatility of equity estimated on a one-year rolling window. See Bharath and Shumway (2008) for details.

the momentum condition in equation (11), for which the model predicts return continuation, and firms that do not, for which momentum is not expected.

Figure A.1 plots the fraction of CRSP stocks that satisfy the momentum condition in equation (11) over the period 1968–2024. On average, approximately 15% of stocks meet the condition, but there is substantial time-series variation. The fraction is elevated during the 1970s and 2010s and markedly lower during the 1980s and 2000s. In addition, the average covariance between changes in realized and expected stock returns (equation (10)) is positive in most sample years (see Figure 4). Taken together, these patterns imply that the model predicts positive momentum in U.S. equities on average, punctuated by occasional periods of reversal or momentum crashes—consistent with the evidence documented by Daniel and Moskowitz (2016)—when the covariance turns negative. We build on these observations in our baseline tests of momentum in U.S. equities.

In further analyses, we control for a range of firm characteristics that have been shown to affect stock returns in general, or momentum returns in particular. Specifically, we include log market equity, book-to-market, gross profitability, and the debt-to-assets ratio from the CRSP/Compustat Merged database; share turnover from CRSP; an indicator for credit ratings from Standard & Poor's; log analyst coverage and analyst forecast dispersion (defined as the standard deviation of analyst EPS forecasts scaled by the mean forecast) from IBES; and indicators for the Fama–French 30 industries.

As a first step, we conduct portfolio sorts in the spirit of Cooper, Gutierrez, and Hameed (2004). Each month, we separate stocks into two subsamples based on whether they satisfy the momentum condition in equation (11), i.e., whether the covariance between changes in realized and expected equity returns is positive or negative. Within each subsample, we further sort stocks into terciles based on the level of this covariance. This procedure yields six groups. Within each group and each calendar month t, we then sort stocks into deciles based on their cumulative return from month $t-12$ to $t-2$. We compute value-weighted decile portfolio returns from t to $t+1$ (skipping month $t-1$), as well as the winners-minus-losers return, which is long the top decile (highest prior return) and short the bottom decile (lowest prior return).

Table 3 reports the results. The first column ("Overall") presents average decile and winners-minus-losers returns for the full CRSP universe.[10] Consistent with the existing literature (e.g., Daniel and Moskowitz, 2016), the average winners-minus-losers return is 98 basis points per month (approximately 12% annualized).

We then report results separately for the six groups defined by the momentum condition and the covariance terciles. The findings closely align with the model's predictions. Momentum is positive and statistically significant only in Groups 4, 5, and 6, where the momentum condition is satisfied, and is indistinguishable from zero in Groups 1, 2, and 3, which do not satisfy the condition. Moreover, the winners-minus-losers spread increases monotonically with the covariance between past returns and changes in expected returns, rising from 0.493% per month in Group 1 to 1.382% per month in Group 6. In the online appendix, we report results based on independent sorts on prior returns and the covariance measure and find an even steeper monotonic pattern, with momentum returns increasing from 0.600% per month in Group 1 to 2.288% per month in Group 6 (Table A.2).

We obtain similar conclusions when we examine intercepts from the Fama and French (1993) three-factor and Fama and French (2016) five-factor models instead of

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

raw returns. Under the three-factor model, the winners-minus-losers intercept is 167 basis points per month for stocks that satisfy the momentum condition (Group 6), compared to 62 basis points for stocks that do not (Group 1). Under the five-factor model, the corresponding intercepts are 118 and 59 basis points per month, respectively.

To assess robustness and ensure that our results are not subsumed by previously documented drivers of momentum, we next run regressions in the spirit of Fama and MacBeth (1973). This approach allows us to jointly control for a large set of candidate variables in the cross section.

Specifically, for each stock i and month t, we define $\bar{r}_{it}$ as the cumulative return from $t-12$ to $t-2$. In Table 5, we regress the return from t to $t+1$ on $\bar{r}_{it}$ interacted with the covariance between changes in realized and expected returns Cov_{it}, while controlling for firm characteristics and their interactions with $\bar{r}_{it}$. The regression specification is:

$$r_{it+1} = \alpha + \beta\, \bar{r}_{it} \times \mathrm{Cov}_{it} + \sum_k \gamma_k x_{kit} + \sum_k \delta_k \bar{r}_{it} \times x_{kit} + \varepsilon_{it}, \tag{19}$$

where x_{kit} includes log market equity, log book-to-market, gross profitability, log debt-to-assets, log share turnover, log analyst coverage, log analyst forecast dispersion, credit rating, and Fama–French 30 industry indicators. These controls capture several stylized facts from the momentum literature, including the concentration of momentum among firms with high credit risk (Avramov, Chordia, Jostova, and Philipov, 2007) and high information uncertainty (Zhang, 2006). As in Fama and MacBeth (1973), we estimate the regression separately each month and conduct inference based on time-series averages of the coefficients.

We find that the coefficient on the interaction term $\bar{r}_{it} \times \mathrm{Cov}_{it}$ is positive and highly statistically significant. The estimates imply that a 1% higher prior return combined with a one-standard-deviation increase in the covariance is associated with an 88 basis point increase in the next-month return. Importantly, for stocks that do not satisfy the momentum condition, prior returns have no statistically significant relationship with future returns. Overall, these results confirm that our baseline findings are robust to controlling for a wide range of alternative drivers of momentum.

3.2 Momentum in U.S. corporate bonds

We next test the implications of the model for momentum in U.S. corporate bonds, based on the bond momentum condition in equation (17) derived in Section 2.3. We take this condition to the data using a comprehensive sample of U.S. corporate bonds from TRACE over the period 2002–2024. To ensure that our tests rely on clean and reliable bond returns, we use the Corporate Bond Factors data repository filtered following the methodology of Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2025).

As discussed in Section 2.3, under our empirically motivated parametrization the model predicts that corporate bond momentum should be absent, and that momentum could only arise under restrictive parameter assumptions. To evaluate this prediction, we compute the model-implied covariance between changes in realized and expected bond returns (equation (16)). According to condition (17), bond momentum should arise only when this covariance is positive. Figure 5 shows that over the period 1968–2024 the average covariance is always non-positive, consistent with the theoretical prediction.[11] The model therefore predicts no momentum in corporate bonds.

We test this implication directly using standard momentum portfolio sorts. We sort both bond-level and firm-level bond returns into deciles based on their own past returns from month $t-12$ to $t-2$, and compute long–short momentum portfolio returns from t to $t+1$. The results are reported in Table 6. Consistent with the model, we find no statistically significant momentum in either bond-level (Column 1) or firm-level (Column 2) returns. These findings support the theoretical prediction and help explain why momentum in corporate bonds is difficult to detect in practice. While Jostova, Nikolova, Philipov, and Stahel (2013) document some evidence of bond momentum, Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2025) show that average monthly bond momentum returns are close to zero and statistically insignificant, in line with our results.

Prior studies (Dick-Nielsen, Feldhütter, Pedersen, and Stolborg, 2025; Jostova, Nikolova, Philipov, and Stahel, 2013) also document that equity momentum predicts corporate bond returns. Our theory delivers joint, testable implications for equity and bond returns, allowing us to assess such spillovers within a unified framework. We therefore examine whether equity momentum predicts bond returns conditional on the equity momentum condition in equation (11).

In Column (3) of Table 6, we sort firm-level bond returns into decile portfolios based on their firms' past equity returns from month $t-12$ to $t-2$, and report bond returns from t to $t+1$. Unconditionally, we find no significant difference between winner and loser bond portfolios. However, once we condition on the equity

[11] Because the bond momentum condition can be expressed using stock- and accounting-level information only, we can estimate the implied covariance between realized and expected bond returns over the CRSP–Compustat sample period 1968–2024, even though bond returns themselves are only observed from 2002 onward.

momentum condition, a sharp pattern emerges.

Specifically, in Table 7, we first split firms into two groups based on whether they satisfy the equity momentum condition in equation (11). Within each group, we further divide firms into terciles based on the covariance between changes in realized and expected equity returns (equation (10)), yielding six portfolios. Within each of these groups, we form bond momentum portfolios using both bond-level and firm-level bond returns, sorted either on past bond returns or on past equity returns.

Panel A reports bond-level momentum portfolios formed on past bond returns, and Panel B reports firm-level bond momentum portfolios formed on past bond returns. Across all six groups, bond momentum returns are predominantly negative and statistically insignificant. Although Groups 5 and 6—those with the strongest equity momentum—exhibit modest positive bond momentum of approximately 57–70 basis points per month (7–8% annualized), these returns are not statistically significant.

Panel C reports firm-level bond returns sorted on past equity returns. In this case, bond returns of winner firms significantly exceed those of loser firms by 87 and 84 basis points per month (approximately 10% annualized) in Groups 5 and 6, respectively. In contrast, the winner–loser spread is indistinguishable from zero in Groups 1 through 4. Taken together, these results indicate that equity momentum predicts corporate bond returns, but only in states where equity momentum is strongest according to our model, while momentum in bonds themselves remains absent even in those states.

4 Momentum crashes

4.1 Economic mechanism and predictability

We now turn to momentum crashes and show that the same mechanism that generates momentum can imply rare but predictable drawdowns in the strategy. When the conditions supporting momentum become widespread across firms, the strategy's exposure shifts toward systematic risk, creating states in which "good" aggregate shocks (e.g., the economy suddenly recovers) can produce large losses.

We consider an economy with N firms $i = 1, \ldots, N$. Firm i has asset value $A_i(t)$ and asset variance $V_i(t)$ evolving under $\mathbb{P}$ as[12]

$$\begin{aligned} \frac{dA_i}{A_i} &= \mu\, dt + \sigma_A^{i,M}\, dW_t^{A,M} + \sigma_A^{i,I}\, dW_t^{A,I}, & (20)\\ dV_i &= \mu_V\, dt + \sigma_V^{i,M} \sqrt{V_i}\, dW_t^{V,M} + \sigma_V^{i,I} \sqrt{V_i}\, dW_t^{V,I}, & (21) \end{aligned}$$

where $\sigma^{i,M}$ denote loadings on aggregate shocks dW^M while $\sigma^{i,I}$ denote loadings on idiosyncratic shocks dW^I. Using the no-arbitrage restrictions from (3) and assuming that idiosyncratic shocks are not priced, equity returns satisfy

$$\begin{aligned} \frac{dE_i}{E_i} = {} & \Big(r_f + \eta_i^A(\mu - r_f) + \eta_i^V \lambda_V\Big) dt + \eta_i^A \sigma_A^{i,M}\, dW_t^{A,M} + \eta_i^V \left(\frac{\sigma_V^{i,M}}{\sqrt{V}_i}\right) dW_t^{V,M} \\ & + \eta_i^A \sigma_A^{i,I}\, dW_t^{A,I} + \eta_i^V \left(\frac{\sigma_V^{i,I}}{\sqrt{V}_i}\right) dW_t^{V,I}, \qquad (22) \end{aligned}$$

where η_i^A and η_i^V are the equity elasticities for which we supress the t index throughout. $\mu - r_f > 0$ and $\lambda_V < 0$ are the prices of aggregate asset and variance risk, and r_f is the risk-free rate. For a diversified N-stock portfolio, the idiosyncratic terms

[12] For ease of readability, we often supress the t-index in this section.

vanish as $N \to \infty$ under the usual cross-sectional independence and moment conditions. Let $\mathcal{W}_t$ and $\mathcal{L}_t$ denote the sets of winner and loser firms at time t. Consider equally-weighted winner and loser portfolios. Hence, the winner and loser portfolio can be expressed as

$$r^{\mathcal{W}}(t) = \frac{1}{N_{\mathcal{W}}} \sum_{i \in \mathcal{W}_t} \frac{dE_i}{E_i} = \Big(r_f + \eta^A_{\mathcal{W}}(\mu - r_f) + \eta^V_{\mathcal{W}} \lambda_V \Big)\, dt + \Delta^A_{\mathcal{W}}\, dW_t^{A,M} + \Delta^V_{\mathcal{W}}\, dW_t^{V,M}, \tag{23}$$

$$r^{\mathcal{L}}(t) = \frac{1}{N_{\mathcal{L}}} \sum_{i \in \mathcal{L}_t} \frac{dE_i}{E_i} = \Big(r_f + \eta^A_{\mathcal{L}}(\mu - r_f) + \eta^V_{\mathcal{L}} \lambda_V \Big)\, dt + \Delta^A_{\mathcal{L}}\, dW_t^{A,M} + \Delta^V_{\mathcal{L}}\, dW_t^{V,M}, \tag{24}$$

where the portfolio-level elasticities η are the cross-sectional averages and the aggregate shock loadings are defined by

$$\Delta^A_{\mathcal{W}} = \frac{1}{N_{\mathcal{W}}} \sum_{i \in \mathcal{W}_t} \eta^A_i \sigma^{i,M}_A, \qquad \Delta^V_{\mathcal{W}} = \frac{1}{N_{\mathcal{W}}} \sum_{i \in \mathcal{W}_t} \eta^V_i \left(\frac{\sigma^{i,M}_V}{\sqrt{V_i}} \right), \tag{25}$$

and analogously for $\Delta^A_{\mathcal{L}}, \Delta^V_{\mathcal{L}}$. The realized momentum return $r^M = r^{\mathcal{W}} - r^{\mathcal{L}}$ is therefore

$$r^M(t) = \mu^M\, dt + \Delta^A\, dW_t^{A,M} + \Delta^V\, dW_t^{V,M}, \tag{26}$$

$$\mu^M(t) = (\eta^A_{\mathcal{W}} - \eta^A_{\mathcal{L}})(\mu - r_f) + (\eta^V_{\mathcal{W}} - \eta^V_{\mathcal{L}})\lambda_V, \tag{27}$$

$$\Delta^A(t) = \Delta^A_{\mathcal{W}} - \Delta^A_{\mathcal{L}}, \qquad \Delta^V(t) = \Delta^V_{\mathcal{W}} - \Delta^V_{\mathcal{L}}. \tag{28}$$

Equations (26)–(28) imply that momentum crash risk is state dependent and predictable. The predictable component of momentum returns, μ^M, varies over time with the cross-sectional difference in equity elasticities to assets and variance between winners and losers ($\eta^A_{\mathcal{W}} - \eta^A_{\mathcal{L}}$ and $\eta^V_{\mathcal{W}} - \eta^V_{\mathcal{L}}$). When these differences are large in absolute magnitude, the strategy's exposure to aggregate asset and variance risks is elevated, generating states in which momentum appears to offer high expected returns but is simultaneously more fragile. Importantly, these same states are characterized by predictable shifts in the strategy's aggregate shock loadings, (Δ^A, Δ^V), which govern the sensitivity of realized returns to common shocks.

Realized momentum crashes occur when positive aggregate shocks are realized in these high-exposure states. In particular, the model predicts that crashes cluster in post-drawdown periods in which loser firms become highly levered and the momentum strategy is effectively short market rebounds, i.e., $\Delta^A < 0$. In such states, positive aggregate asset shocks ($dW_t^{A,M} > 0$) generate large negative momentum returns through the leverage (asset-shock) channel. Variance declines amplify crashes when $\Delta^V \geq 0$, whereas for $\Delta^V < 0$ the leverage channel must dominate.

Finally, crash risk is increasing in the fraction of firms satisfying the momentum condition. A higher fraction strengthens diversification, eliminating idiosyncratic components and leaving systematic shocks as the primary driver. At the same time, the fraction is itself state dependent and tends to rise in adverse economic conditions—for example when leverage is elevated and/or aggregate variance is high—so it also acts as a sufficient statistic for the prevailing stress state of the economy. In such states, cross-sectional asymmetries between winners and losers become more pronounced (e.g., in aggregate shock loadings), making extreme relative performance more likely when large common shocks arrive.

While the occurrence of a crash ultimately depends on the realization of a positive aggregate shock and is therefore an empirical question, the model implies that differences in the loadings on that shock between winners and losers are a necessary condition for momentum to crash. We analyze the behavior of these shock loadings and the fraction of firms satisfying the momentum condition in a simulated crash environment. Specifically, after a series of negative aggregate asset shocks (the "economic crisis"), we impose a rapid recovery by setting the aggregate asset shock $dW_t^{A,M}$ to be large and positive and the aggregate variance shock $dW_t^{V,M}$ to be negative. The recovery is triggered once the rolling sum of the past two months' daily asset shocks falls below -1, which corresponds to approximately a 2.5σ event for the 60-day Brownian shock.

Figure 6 shows the results. Panel A highlights that the combined shock loading $\Delta^A + \Delta^V$ is negative when the economy is in a crisis and in the periods leading up to the momentum crash. This pattern is mainly driven by the loadings on assets: the absolute value of Δ^A is roughly an order of magnitude larger than the absolute value of Δ^V. The negative sign of $\Delta^A + \Delta^V$ is attributable to the fact that losers tend to be more distressed after negative past performance, which increases their asset return elasticity $\eta_A = \frac{A}{E} E_A$ more than for winners. Panel B shows that, before the economy recovers and momentum crashes, the fraction of firms satisfying our momentum condition increases gradually. Panel C plots the return of the momentum portfolio. While the magnitude of the crash is mechanically determined by the size of the imposed recovery shock, the key point is that even relatively small asymmetries in the shock loadings are sufficient to generate substantial momentum crashes.

4.2 Empirical evidence on momentum crashes

Next, we test empirically our model predictions regarding momentum crashes. We define a momentum crash as an indicator equal to one when the momentum return lies in the bottom 5% of its unconditional distribution over 1968–2024. We estimate:

$$\Pr(\text{Crash}_{t+1}) = \alpha_k + \beta_k X_{k,t} + \varepsilon_{k,t+1}, \qquad X_{k,t} \in \{\mu^M,\ \omega_t,\ \Delta^A,\ \Delta^V\}, \tag{29}$$

where μ^M is the model-implied expected momentum return from (27), ω_t is the fraction of firms satisfying the momentum condition, and Δ^A and Δ^V are the exposures of the momentum strategy to unexpected systematic asset and variance shocks. Each regressor $X_{k,t}$ is included in a separate regression or in combination with ω_t.

To construct μ^M, Δ^A and Δ^V we need firm-level elasticities η_i^A, η_i^V and loadings $\sigma_A^{i,M}, \sigma_V^{i,M}$. We use the same elasticities as in Section 3.1. For the loadings, we follow Doshi, Jacobs, Kumar, and Rabinovitch (2019), we estimate unlevered $\sigma_A^{i,M}$ using 2-year rolling regressions:

$$r_{i,t} = \alpha_{i,t} + \sigma_A^{i,M}\, r_t^m \left(1 + \frac{F_{i,t-1}(1-\theta)}{E_{i,t-1}}\right) + \epsilon_{i,t}, \tag{30}$$

where r_t^i is the stock return, $F_{i,t-1}$ and $E_{i,t-1}$ are lagged debt face value and equity market value, r_t^m is the market return, and $\theta = 20\%$ is the corporate tax rate. We estimate $\sigma_V^{i,M}$ by regressing firm variance innovations on market variance innovations in 2-year rolling windows:

$$\Delta V_{i,t} = \alpha_{i,t} + \sigma_V^{i,M}\, \Delta V_t^m + u_{i,t}. \tag{31}$$

We then average estimates within winner and loser portfolios. Again, we fix $\mu - r_f = 4\%$ and $\lambda_V = -1.5$.

Panel A of Table 8 shows that momentum crashes are predictable. Crash risk rises sharply when the fraction of firms satisfying the momentum condition, ω_t, is high, indicating that the strategy is increasingly exposed to aggregate shocks. The expected momentum return, μ^M, also positively predicts crash risk, implying that periods of high predicted returns coincide with heightened fragility. Economically, a one–standard–deviation increase in either μ^M or ω_t raises crash probability by about 5 percentage points. Consequently, when ω_t doubles or triples prior to crashes, the predicted crash probability rises from about 5% to roughly 15–20%. Columns (3) and (4) highlight the role of aggregate shock exposures. The asset-shock loading Δ^A enters negatively and significantly, indicating that crashes become more likely when momentum is effectively short market rebounds, while the variance-shock loading Δ^V is small and statistically insignificant.

In Panel B, negative coefficients on the elasticity spreads $\eta^A_{\mathcal{W}} - \eta^A_{\mathcal{L}}$ and $\eta^V_{\mathcal{W}} - \eta^V_{\mathcal{L}}$ imply greater aggregate shock sensitivity of losers, endogenously increasing leverage on the short leg of momentum and amplifying crash risk. Additionally, increases in losers' asset-shock loading ($\Delta^A_{\mathcal{L}}$) significantly raise crash risk, while variance- shock contributions from both winners and losers are weaker and generally insignificant. Overall, the evidence supports the model's prediction that momentum crashes are forecastable and arise in states characterized by large leverage asymmetries and elevated losers' exposure to aggregate asset shocks, consistent with Daniel and Moskowitz (2016).

5 Conclusion

We propose a structural explanation for momentum grounded in the Merton (1974) framework augmented with implied stochastic volatility (Aït-Sahalia, Li, and Li, 2020; Carr and Wu, 2020). The model highlights a fundamental interaction between leverage and variance: equity's option-like structure implies that even when total asset returns are independent and identically distributed, equity returns need not be. When the variance 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 simple, closed-form criterion for 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 strongly support the model's key predictions. U.S. equity momentum is concentrated among firms that satisfy the model-implied condition, and momentum strength 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.

Importantly, the model provides a structural explanation for momentum crashes. Periods with high expected momentum returns and a large fraction of firms satisfying the momentum condition coincide with elevated exposure of the strategy to aggregate shocks. In these states, increasing leverage among loser stocks induces a negative loading to aggregate asset shocks, so that market rebounds generate large losses. Empirically, this mechanism is reflected in the strong predictive power of systematic exposure, with the leverage channel and the short leg driving crash risk.

Finally, the model delivers sharp predictions beyond equities. In corporate bonds, empirically plausible parameter values imply little aggregate momentum, consistent with evidence from clean bond return data. At the same time, equity momentum predicts bond returns only among firms whose equity satisfies the model's momentum condition. Taken together, the theory and evidence show 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 momentum crashes occur—and when momentum should not be expected to arise.

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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 $m = A_t / Fe^{-r\tau}$ and note that $E_A = \frac{\partial E_t}{\partial A_t} = \Phi(d_1)$ is the standard Black-Scholes delta. Therefore,

$$\eta_t^A = \Phi(d_1)\frac{A_t}{E_t} = \left[\frac{A_t\Phi(d_1) - Fe^{-r\tau}\Phi(d_2)}{A_t\Phi(d_1)}\right]^{-1} = \left[1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right]^{-1}. \tag{32}$$

Hence, we get that

$$\begin{aligned}
\frac{\partial \eta_t^A}{\partial A_t} &= \frac{E_A + A_t E_{AA}}{E_t} - \frac{A_t E_A^2}{E_t^2} && (33)\\
&= \frac{\partial}{\partial A_t}\left(\frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right) && (34)\\
&= \frac{Fe^{-r\tau}}{A_t} \times \left[\frac{\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1)}{A_t(\Phi(d_1))^2 V_t\sqrt{\tau}} - \frac{\Phi(d_2)}{A_t\Phi(d_1)}\right] && (35)\\
&= \frac{1}{m} \times \frac{\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1) - \Phi(d_1)\Phi(d_2)V_t\sqrt{\tau}}{A_t(\Phi(d_1))^2 V_t\sqrt{\tau}}, && (36)
\end{aligned}$$

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:

$$\frac{\partial \eta_{A,t}}{\partial A_t} = \frac{\partial}{\partial A_t}\left[\left(1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right)^{-1}\right] = \frac{\frac{1}{m} \times \frac{\varphi(d_2)\Phi(d_1) - \Phi(d_2)\varphi(d_1) - \Phi(d_1)\Phi(d_2)V_t\sqrt{\tau}}{A_t\Phi(d_1)^2 V_t\sqrt{\tau}}}{\left(1 - \frac{1}{m} \times \frac{\Phi(d_2)}{\Phi(d_1)}\right)^2}. \tag{37}$$

Since $1/m > 0$, $A_t\Phi(d_1)^2 V_t\sqrt{\tau} > 0$, 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:

$$\frac{\varphi(d_2)}{\Phi(d_2)} - \frac{\varphi(d_1)}{\Phi(d_1)} < V_t\sqrt{\tau} \tag{38}$$

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:

$$\int_{d_2}^{d_1} |h'(x)|dx < \int_{d_2}^{d_1} |1|dx = |d_1| - |d_2| = d_1 - d_2 = s. \tag{39}$$

But then:

$$h(d_2) - h(d_1) = \left|\int_{d_2}^{d_1} h'(x)dx\right| \leq \int_{d_2}^{d_1} |h'(x)|dx < s, \tag{40}$$

where the inequality is the well-known result for the absolute value of a definite integral. Therefore, if $|h'(d)| < 1$, condition (38) 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 $h'(x) = -h(x)\left[x + h(x)\right] < 0$.

(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:

$$\frac{\varphi(x)}{\Phi^2(x)}f(x) = \frac{\varphi(x)}{\Phi^2(x)}f(x)\left[\frac{\varphi'(x)}{\varphi(x)}\Phi(x) - \varphi(x) + \frac{\Phi^2(x)}{\varphi(x)}\right] = \frac{\varphi'(x)\Phi(x) - \varphi^2(x)}{\Phi^2(x)} = h'(x)+1. \tag{41}$$

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

$$\begin{aligned} f'(x) = -\Phi(x) - x\varphi(x) + x\varphi(x) + \frac{2\Phi(x)\varphi(x) + x\Phi^2(x)}{\varphi(x)} = \\ -\Phi(x) + 2\Phi(x) + x\frac{\Phi^2(x)}{\varphi(x)} = \Phi(x)\left[1 + \frac{x}{h(x)}\right]. \end{aligned} \tag{42}$$

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

$$\frac{\partial \eta_t^V}{\partial A_t} = \frac{V_t(E_{AV}E - E_V E_A)}{E_t^2} < 0. \tag{43}$$

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:

$$\eta_t^V = \frac{A_t}{E_t}\varphi(d_1)V_t\sqrt{\tau} = \eta_t^A\frac{\varphi(d_1)}{\Phi(d_1)}V_t\sqrt{\tau}. \tag{44}$$

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

$$
\begin{aligned}
\frac{\partial \eta_t^V}{\partial A_t} = \frac{\partial}{\partial A_t}\left(\eta_t^A \frac{\varphi(d_1)}{\Phi(d_1)} V_t\sqrt{\tau}\right) \quad &< \quad 0 \\
\Leftrightarrow V_t\sqrt{\tau}\left(\frac{\partial \eta_t^A}{\partial A_t}\frac{\varphi(d_1)}{\Phi(d_1)} + \eta_t^A \frac{\partial}{\partial A_t}\left(\frac{\varphi(d_1)}{\Phi(d_1)}\right)\right) \quad &< \quad 0
\end{aligned} \tag{45}
$$

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

$$
\frac{\partial \eta_t^A}{\partial V_t} = \frac{A_t(E_{AV}E - E_V E_A)}{E_t^2} \tag{46}
$$

which is the almost the same expression as in (43) 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

$$
\frac{\partial \eta_t^V}{\partial V_t} = \frac{E_V + V_t E_{VV}}{E_t} - \frac{V_t E_V^2}{E_t^2} \tag{47}
$$

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

$$
\Big(e^n \Phi(d_1) - \Phi(d_2)\Big)\Big(d_1 d_2 + 1\Big) > e^n V_t \sqrt{T}\phi(d_1), \tag{48}
$$

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

Figures and Tables

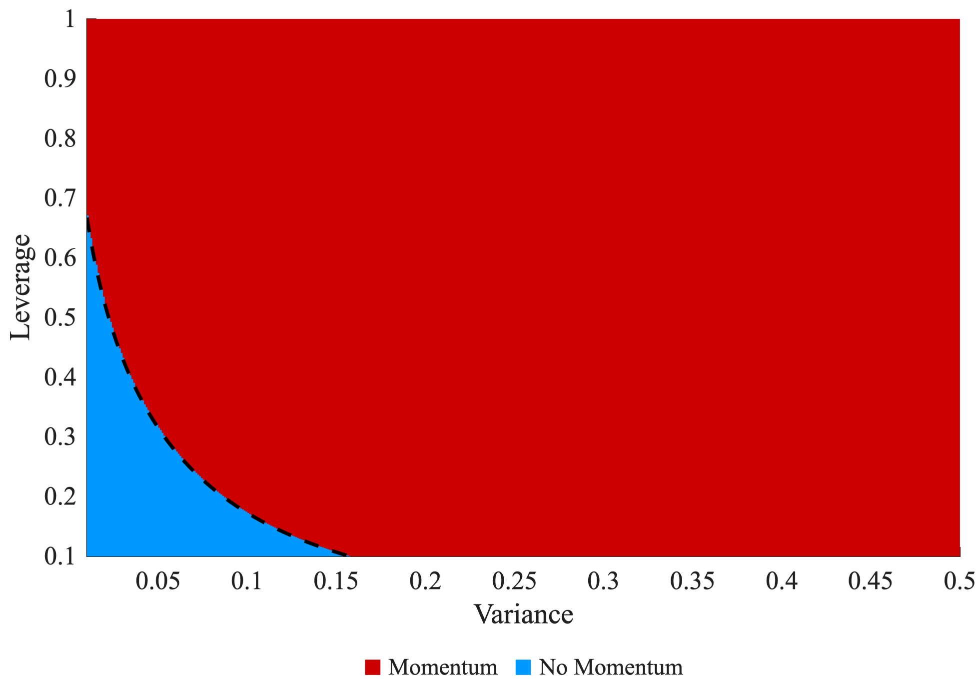

Figure 1. Sensitivity of equity momentum condition
The figure plots the sign of $\text{Cov}_t\,(dg, r)$ from Equation (10) as a function of leverage F/A and variance V. The red (blue) area are states where Cov_t is positive (negative), implying momentum (no momentum). We use the following annualized parameters: asset risk premium $\mu - r_f = 4\%$, 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 $\rho = -0.7$.

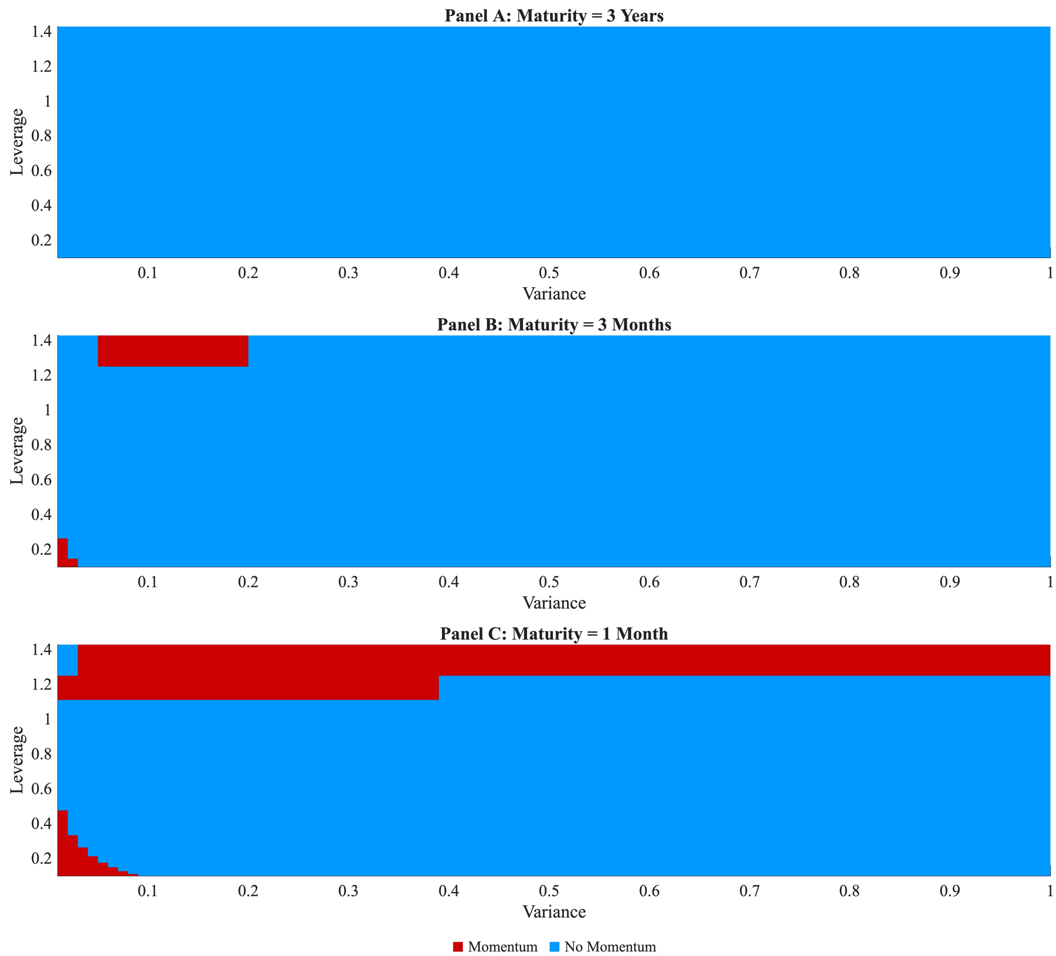

Figure 2. Sensitivity of bond momentum condition
The figure plots the sign of $\mathrm{Cov}_t\left(dg^D, r^D\right)$ from Equation (16) as a function of leverage F/A and variance V. The red (blue) area are states where Cov_t is positive (negative), implying momentum (no momentum). Panel A plots the condition 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 $\mu - r_f = 4\%$, 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 $\rho = -0.7$.

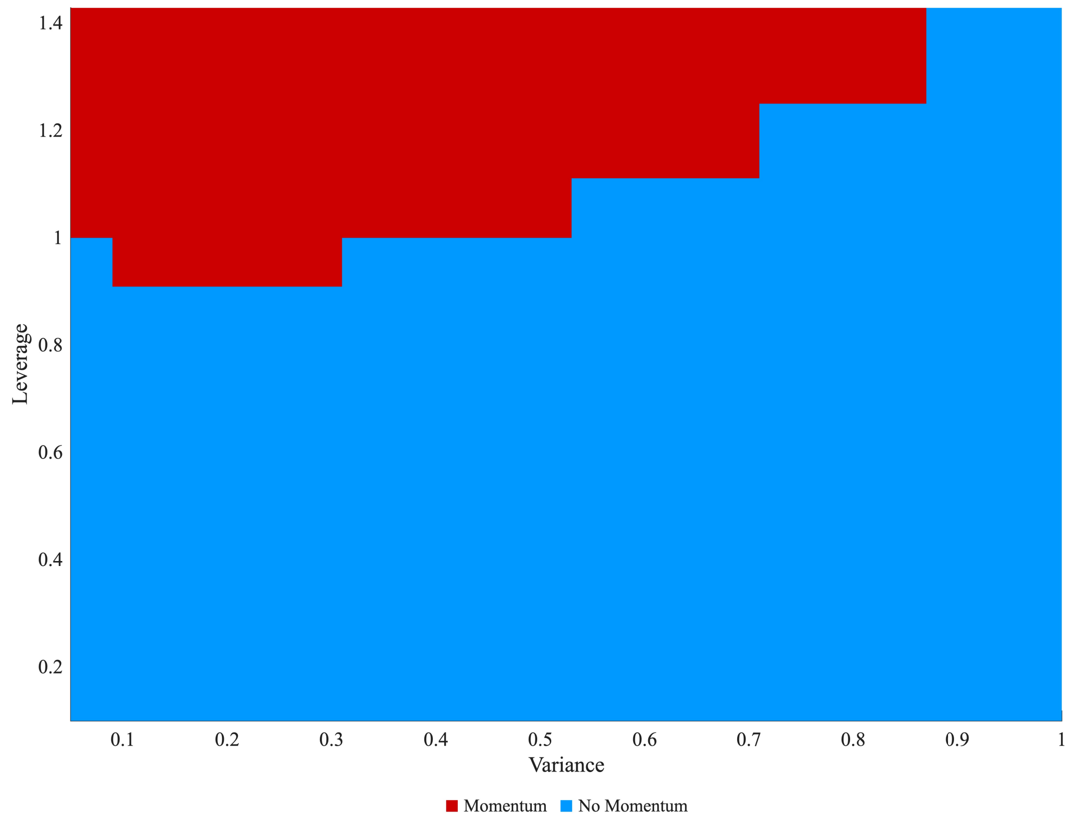

Figure 3. Covariance between past equity and expected bond returns
The figure plots the sign of $\mathrm{Cov}_t\left(dg^D, r\right)$ from Equation (18) as a function of leverage F/A and variance V. The red (blue) area are states where Cov_t is positive (negative), implying momentum (no momentum). We use the following annualized parameters: asset risk premium $\mu - r_f = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, and correlation between the assets and implied variance shocks $\rho = -0.7$.

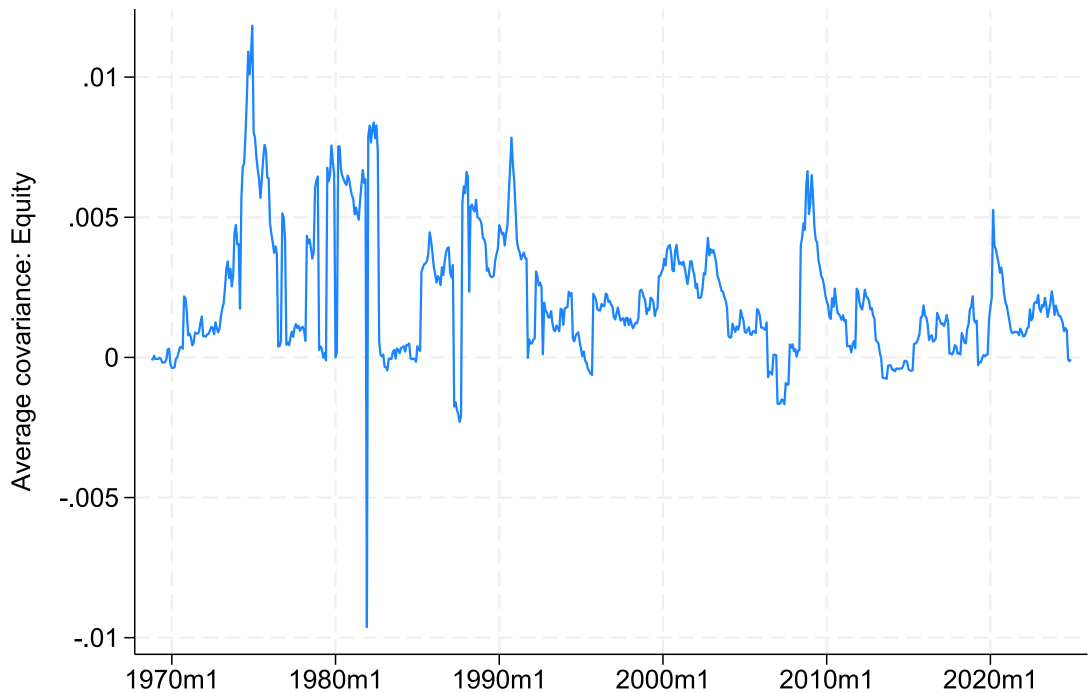

Figure 4. Average covariance in U.S. equities
The figure shows the average covariance between changes in realized and expected stock returns (equation (10)) in the CRSP firms' equity sample over the period 1968–2024.

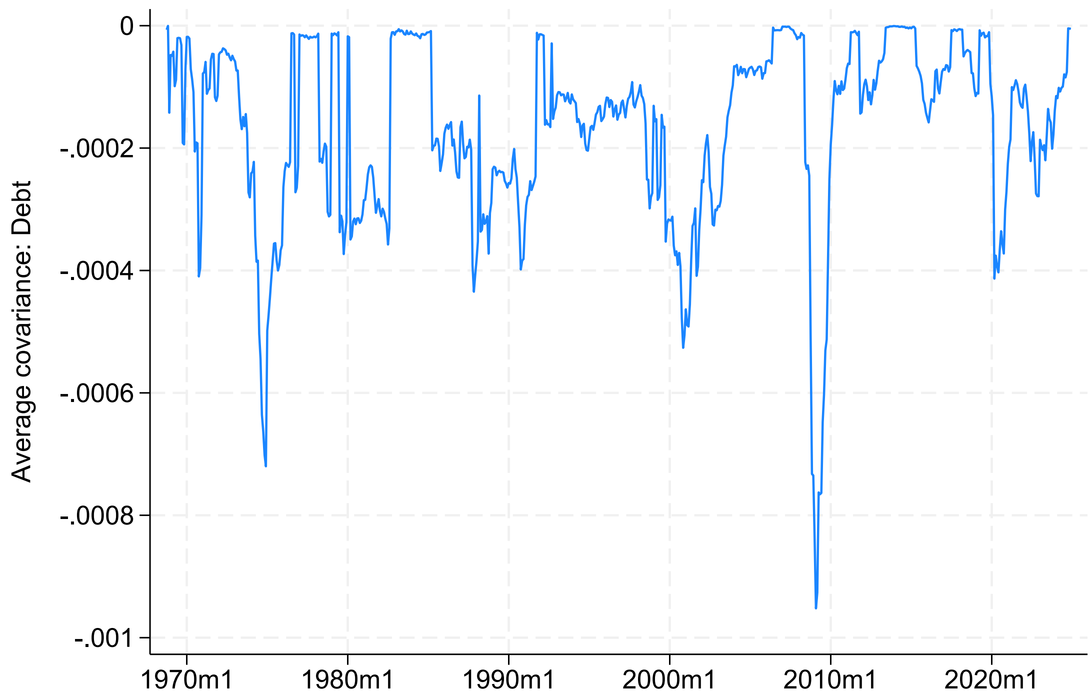

Figure 5. Average covariance in U.S. debt
The figure shows the average covariance between changes in realized and expected debt returns (equation (16)) in the CRSP firms' debt sample over the period 1968–2024.

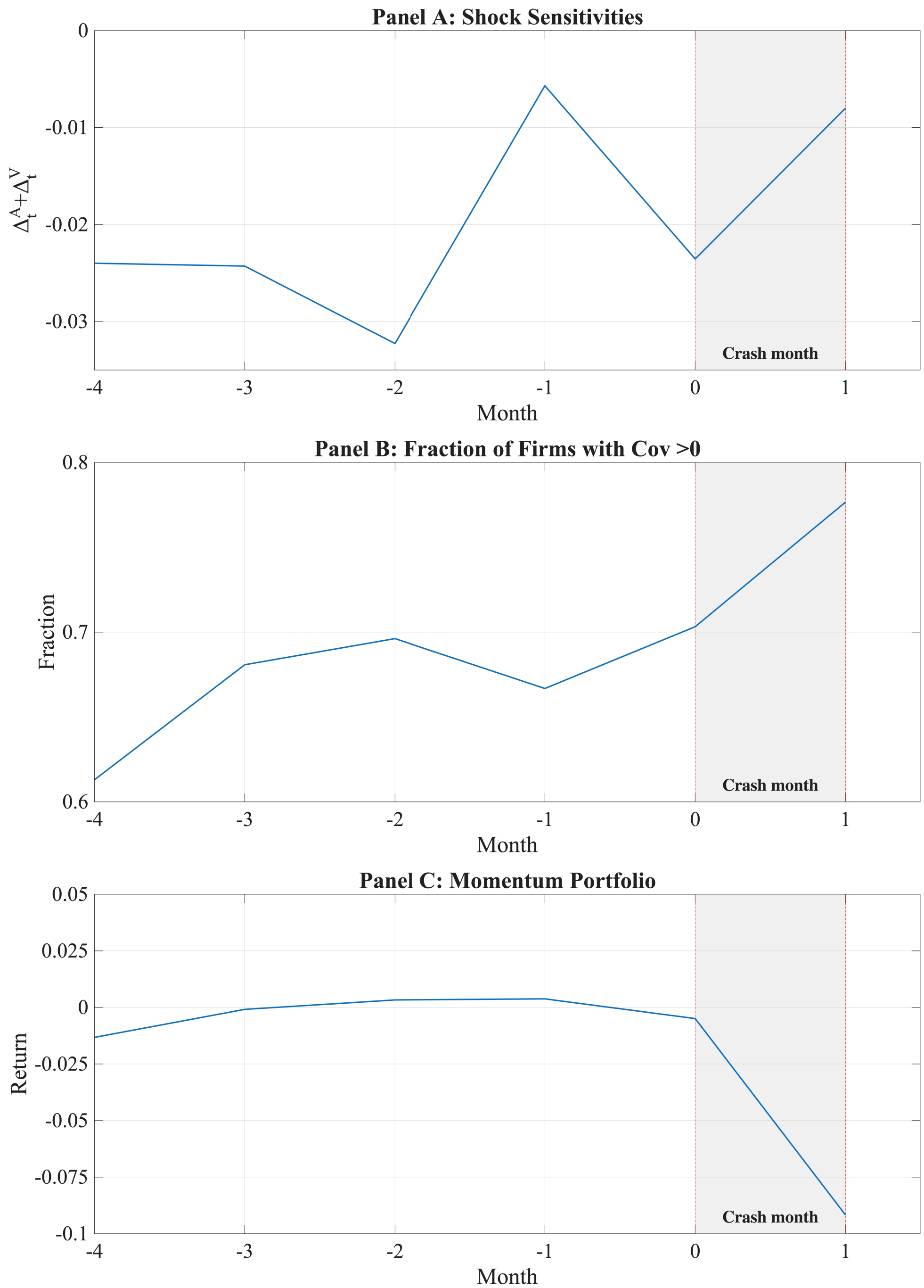

Figure 6. Simulation of Momentum Crashes
The figure shows the shock sensitivities $\Delta_t^A + \Delta_t^V$ in Panel A, the fraction of firms satisfying the momentum condition $\mathrm{Cov}_t\,(dg, r) > 0$ in Panel B, and the return of the momentum portfolio in Panel C for simulated momentum crashes. The momentum crash is simulated by imposing a large positive (negative) asset (variance) shock if the sum of the past two month daily asset shocks exceeds -1, an approx. 2.5σ event.

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 and variance V 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 $\mathrm{Cov}_t > 0$, 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 $F = [10; 90]$, $\sigma_A = 0.10$, $\sigma_V = 0.20$, $\rho = -0.7$, $\kappa^{\mathbb{P}} = 3$, $\theta^{\mathbb{P}} = 0.05$, $\lambda_{IV} = -1.5$, fixed time-to-maturity $\tau = 3$, return on assets $\mu = 7\%$, and risk-free rate $r_f = 3\%$. All firms at the start are identical with assets $A(0) = 100$ and $V(0) = 0.07$.

Portfolio	Mean	Std	1$^{\text{st}}$ Pct	25$^{\text{th}}$ Pct	75$^{\text{th}}$ Pct	99$^{\text{th}}$ 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 and variance V 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 $\mu - r_f$			
	$\mu = 0.05$	$\mu = 0.08$	$\mu = 0.14$	$\mu = 0.17$
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 raw returns on portfolios sorted based on prior return deciles. Each calendar month t the sample of all CRSP common stocks in the period 1968–2024 is split based on whether they satisfy the momentum condition in equation (11), that is whether the covariance between changes in realized and expected equity returns is positive or negative. Within each subsample stocks are then sorted into terciles by the magnitude of this covariance, yielding six groups from lowest (Group 1) to highest (Group 6) covariance. In each group and month t, stocks are further sorted into deciles based on their $t-12$ to $t-2$-month return. We report value-weighted decile portfolio returns from t to $t+1$ (skipping month $t-1$), as well as the winners-minus-losers (P10–P1) return. In the first "Overall" column stocks are sorted in deciles only based on their past $t-12$ to $t-2$-month return. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r_f = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, 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)
P2	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)
P3	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)
P4	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)
P5	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)
P6	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)
P7	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)
P8	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)
P9	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. Each calendar month t the sample of all CRSP common stocks in the period 1968–2024 is split based on whether they satisfy the momentum condition in equation (11), that is whether the covariance between changes in realized and expected equity returns is positive or negative. Within each subsample stocks are then sorted into terciles by the magnitude of this covariance, yielding six groups from lowest (Group 1) to highest (Group 6) covariance. In each group and month t, stocks are further sorted into deciles based on their $t-12$ to $t-2$-month return. We report value-weighted decile portfolio risk-adjusted returns of P1 (losers) and P10 (winners) from t to $t+1$ (skipping month $t-1$), as well as the winners-minus-losers (P10–P1) return. 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. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r_f = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, 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 $r_{it+1} = \alpha + \beta \bar{r}_{it} \times \mathrm{Cov}_{it} + \sum_k \gamma_k x_{kit} + \sum_k \delta_k \bar{r}_{it} \times x_{kit} + \varepsilon_{it}$, 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 (10)). We include various determinants of momentum x_{kit}: 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, 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 $\mu - r_f = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, 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 $t+1$ sorted based on their own past $t-12$ to $t-2$-month return. In Column (2) firm-level bond returns are sorted based on their own past $t-12$ to $t-2$-month return and in 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 (P10–P1) 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)
P2	0.334	0.335	0.377
	(2.33)	(2.65)	(3.08)
P3	0.221	0.330	0.365
	(1.54)	(2.61)	(2.98)
P4	0.214	0.234	0.360
	(1.50)	(1.85)	(2.94)
P5	0.212	0.269	0.362
	(1.48)	(2.13)	(2.96)
P6	0.221	0.275	0.353
	(1.54)	(2.18)	(2.89)
P7	0.229	0.275	0.324
	(1.60)	(2.18)	(2.65)
P8	0.246	0.300	0.352
	(1.72)	(2.38)	(2.88)
P9	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

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	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 of a 0/1 indicator for overall momentum crashes in the CRSP 1968-2024 sample of common stocks that takes the value of 1 if the winners-loser portfolio returns are below the 5^{th} bottom percentile of the distribution. In Panel A the explanatory variables are the expected momentum return μ^M, the fraction of stocks satisfying the momentum condition ω_t, and the momentum return loading to asset and variance shocks. Panel B shows the momentum crash predictors' decomposition based on equation (26). The table reports the coefficient estimates and the t-statistics based on robust standard errors in parentheses below.

	Panel A: Momentum crash predictors			
	(1)	**(2)**	**(3)**	**(4)**
Expected momentum return (μ^M)	1.320			
	(3.62)			
Fraction ω_t satisfying momentum condition		0.470	0.406	0.415
		(4.19)	(3.63)	(3.60)
Asset shock asymmetry: Δ^A			-0.028	
			(-2.04)	
Variance shock asymmetry: Δ^V				-0.999
				(-1.31)
R^2	0.060	0.056	0.066	0.064
N	671	674	671	671

	Panel B: Momentum crash predictors' decomposition					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Assets: $\eta^A_{\mathcal{W}} - \eta^A_{\mathcal{L}}$	-0.077					
	(-2.51)					
Variance: $\eta^V_{\mathcal{W}} - \eta^V_{\mathcal{L}}$		-1.711				
		(-3.71)				
Losers asset loading $\Delta^A_{\mathcal{L}}$			0.031			
			(1.69)			
Winners asset loading $\Delta^A_{\mathcal{W}}$				-0.050		
				(-2.18)		
Losers variance loading $\Delta^V_{\mathcal{L}}$					0.628	
					(0.86)	
Winners variance loading $\Delta^V_{\mathcal{W}}$						-1.270
						(-1.79)
Fraction ω_t satisfying momentum condition			0.411	0.449	0.428	0.486
			(3.58)	(4.08)	(3.53)	(4.19)
R^2	0.010	0.057	0.063	0.064	0.058	0.064
N	671	671	671	671	671	671

Online Appendix

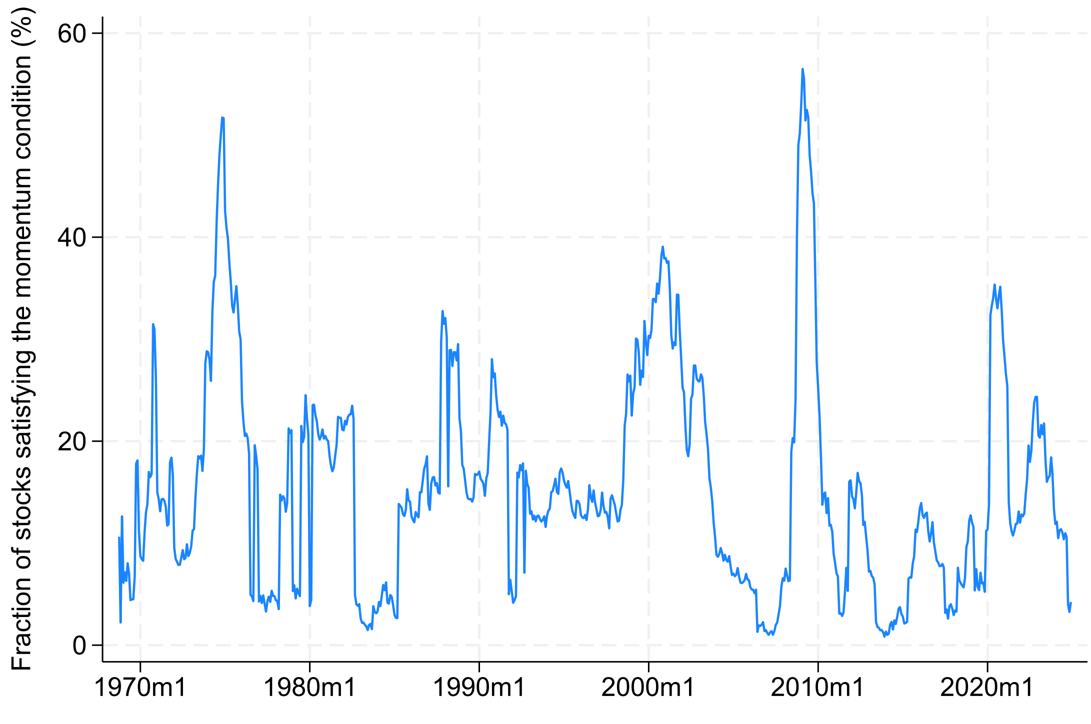

Figure A.1. Percentage of U.S. equities satisfying the momentum condition
The figure shows the ratio of the number of stocks satisfying the momentum condition (equation (11)) to the number of stocks in the CRSP database over the period 1968–2024.

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 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 $r_f = 3\%$. 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, the sample of CRSP common stocks from 1968–2024 is first split based on whether they satisfy the momentum condition in equation (11), that is, whether the covariance between changes in realized and expected equity returns is positive or negative. Within each subsample, stocks are then sorted into terciles by the magnitude of this covariance, yielding six groups from lowest (Group 1) to highest (Group 6) covariance. Independently, in each month t, stocks are sorted into deciles based on their cumulative returns from $t-12$ to $t-2$. The intersection of the group and return sorts defines the portfolios. We report value-weighted decile returns from t to $t+1$ (skipping month $t-1$), as well as the winners-minus-losers (P10–P1) return. In the first "Overall" column stocks are sorted in deciles only based on their past $t-12$ to $t-2$-month return. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r_f = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, 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)
P2	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)
P3	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)
P4	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)
P5	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)
P6	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)
P7	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)
P8	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)
P9	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.3. 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 the sample of all CRSP common stocks in the period 1968–2024 is split based on whether they satisfy the momentum condition in equation (11), that is whether the covariance between changes in realized and expected equity returns is positive or negative. Within each subsample stocks are then sorted into terciles by the magnitude of this covariance, yielding six groups from lowest (Group 1) to highest (Group 6) covariance. In each group and month t, stocks are further sorted into deciles based on their $t-12$ to $t-2$-month return. We report value-weighted decile portfolio returns from t to $t+1$ (skipping month $t-1$), as well as the winners-minus-losers (P10–P1) return. In the first "Overall" column stocks are sorted in deciles only based on their past $t-12$ to $t-2$-month return. Consistent with our model we fix the following annualized parameters in the estimation of the momentum condition: asset risk premium $\mu - r_f = 4\%$, variance risk premium $\lambda = -1.5$, asset volatility $\sigma_A = 0.10$, implied variance volatility $\sigma_V = 0.20$, 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)
P2	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)
P3	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)
P4	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)
P5	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)
P6	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)
P7	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)
P8	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)
P9	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)