

Fundamental Volatility

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Abstract

This study documents a novel finding that fundamental volatility measured from financial statement variables negatively predicts stock returns, an effect that is strikingly pervasive (over a large number of accounting variables) and persistent (predicting returns over at least two years). A long-short portfolio based on fundamental volatility generates a significantly positive monthly return of 0.93% and significant alphas under a variety of factor models including the Fama-French five-factor model and the q-factor model. We propose a production-based asset pricing explanation to this high-volatility/low-return phenomenon. In the model, due to diminishing marginal return to inputs, firms with higher operating volatility have lower expected profitability and lower expected returns. Further empirical analyses confirm two key predictions of the model. First, the effect of fundamental volatility on stock return is mainly through the profitability channel. Second, the negative effect of fundamental volatility on both profitability and return is stronger for firms facing more severe diminishing marginal returns in their operations.

Keywords: Fundamental volatility; production-based asset pricing; multi-factor models

JEL Classification: G14

1 Introduction

The relation between risk and return is a central and long-standing question in asset pricing. Early empirical efforts to tackle this question date back to the time shortly after the birth of modern asset pricing theories; for example, Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973). This long stream of research has resulted in an intriguing discovery: high risk is often associated with low return, most prominently in the forms of the idiosyncratic volatility anomaly and the betting-against-beta anomaly; see, e.g., Ang, Hodrick, Xing, and Zhang (2006; 2009) and Frazzini and Pedersen (2014). Notably, in these studies, risk — be it volatility or beta — is measured from stock returns.

This study examines the effect of volatility in corporate fundamentals on stock returns. Our interest in fundamental volatility is motivated in part by research pioneered by Campbell and Shiller (1988) and Campbell (1991), which highlights the distinction between two components of asset returns, one driven by shocks to corporate fundamentals (i.e., cash-flow news) and another driven by variations in expected returns (i.e., discount-rate news). Subsequent studies, such as Campbell and Vuolteenaho (2004), Campbell, Polk and Vuolteenaho (2010), Penman and Yehuda (2019), Lochstoer and Tetlock (2020), have used this distinction to understand various asset pricing effects, notably the size and value anomalies. This paper asks to what extent the puzzling high-volatility/low-return phenomenon can be attributed to the volatility of corporate fundamentals.

Empirically, we find a negative relation between fundamental volatility and subsequent stock returns that is strong, pervasive, and persistent. We measure fundamental volatility (FVOL hereafter) using the standard deviations of 14 financial statement items that represent major resources or inputs used in corporate operations, such as total assets and cost of goods sold. Most of these FVOL measures significantly predict stock returns. A long-short value-weighted decile portfolio based on the average ranks of the 14 FVOL measures generates a monthly return of 0.93% ($t = 4.09$) during the quarter after portfolio formation and significant alphas under a wide range of factor models such as CAPM, the Fama-French (1992) three-factor alpha model, the Carhart (1994) four-factor model, the Fama-French

five-factor model, and the q-factor model of Hou, Xue, and Zhang (2015). Moreover, the returns and alphas of the long-short portfolio are significant for at least 8 quarters after formation. On average, by the 8th quarter, FVOL retains more than 80% of its predictive power from the first quarter after formation, suggesting a long-lasting FVOL effect.

The effect of fundamental volatility is similar to, but in many ways stronger than, that of idiosyncratic stock return volatility (IVOL). The IVOL anomaly is in the form of extremely low returns to stocks with very high volatility while no abnormal returns to stocks with low volatility. By contrast, low- and high-FVOL stocks have significantly positive and negative alphas, respectively. Further, high-IVOL stocks are extremely small by marketcap and low-IVOL stocks extremely large, whereas the size difference between the low- and high-FVOL stocks is much more modest. Moreover, the return-predictive horizon of FVOL is much longer than that of IVOL (i.e., over 8 quarters vs. 1 quarter). While the IVOL anomaly is readily absorbed by multi-factor models that include a profitability factor, the FVOL-return relation is not. Finally, based on double-sorted portfolios, we find that the FVOL-return relation remains significant after controlling for IVOL.

Existing studies have found a robust positive premium to risk measures based on corporate fundamentals, such as the cash flow beta by Campbell and Vuolteenaho (2004). The negative FVOL-return relation suggests that FVOL is conceptually different from the cash flow beta. We also note that popular hypotheses on the IVOL anomaly, especially those based on market frictions and investor behavior, are either not directly applicable or too restrictive to explain the fundamental volatility effect.

In search for an explanation, we resort to a production based asset pricing model that relates firm characteristics to stock returns. The model assumes no investor biases and no frictions in financial markets, but incorporates a realistic form of friction in the production sector — diminishing marginal return to production inputs. To illustrate the idea, consider a firm that wishes to increase production but cannot quickly install new equipment. It may resort to hiring more labor as an imperfect substitute; however, the marginal labor productivity and the marginal profitability of capital would likely decline. Such diminishing

return to inputs can be conveniently modeled by the concavity of the production function, which in turn implies that volatility of production inputs has a negative impact on expected profitability. We embed this concavity effect in an asset pricing model to show that higher fundamental volatility leads to both lower profitability and lower stock returns. The model can further generate a negative relation between stock return volatility and expected stock return, suggesting that, from a theoretical perspective, the FVOL and IVOL effects share the same economic origin.

A unique prediction of the model is that fundamental volatility negatively forecasts corporate profitability. Further empirical analysis provides strong support to this prediction. Using three profitability measures from the literature, i.e., gross profit (Novy-Marx 2013), operating profit (Fama and French 2015), and return on equity (Hou, Xue, and Zhang 2015), we show that increasing FVOL by one percentile significantly reduces these profit measures during the subsequent quarter by 0.02% to 0.04%. Further, fundamental volatility has significant predictive power for profitability over long horizons, i.e. at least during the subsequent 8 quarters. These results are robust to controlling for past profitability as well as an extensive set of firm characteristics commonly used to predict profitability (e.g., Fama and French 2006).

To assess the extent to which the FVOL-profitability relation explains the FVOL-return relation in competition with other firm characteristics, we follow Hou and Loh (2016) to decompose the contributions of candidate explanatory variables in a multivariate regression framework. The candidate variables include profitability measured contemporaneously with stock returns (as predicted by the model), as well as lagged firm characteristics such as IVOL, maximum and skewness of returns, illiquidity, size, book-to-market ratio, firm age, asset growth, past profitability, earnings surprise, and accruals. When contemporaneous profitability is excluded, between 30% and 60% of the FVOL-return relation remains unexplained by the rest of candidate variables collectively. However, once contemporaneous profitability is included, the negative FVOL-return relation is almost completely explained away. There is also a similar result for the IVOL-return relation. These findings under-

score the importance of the contemporaneous profitability channel in explaining the high-volatility/low-return phenomenon.

We perform three additional sets of analyses to further understand the FVOL effect.

First, in our model, low-FVOL stocks have higher returns implicitly because they bear higher risk exposure. Although the model does not identify the exact source of risk associated with FVOL, we find that FVOL and profitability likely load on the same set of systematic risk in the financial market. In the time series, the Low-High FVOL portfolio returns (and the Low-High IVOL portfolio returns) are highly correlated with the profitability factors of Fama and French (2015) and Hou, Xue, and Zhang (2015). Furthermore, they vary strongly and in similar ways across business cycles.

Second, we show that the concavity of the production function affects the magnitude of the FVOL effect. For firms facing a more concave production function, the effects of FVOL on profitability and on stock returns are both stronger, i.e., more negative. This finding lends further support to the model.

Finally, we evaluate the FVOL effect in the context of a factor zoo; that is, against a large set of asset pricing factors documented in existing studies. Following the double-selection approach of Feng, Giglio, and Xiu (2020), we find that the FVOL-return relation remains significant in such tests, highlighting the unique information content of FVOL for predicting stock returns.

This paper contributes to several strands of the literature. It is related to the literature on the low-volatility anomaly documented by Haugen and Baker (1996), Ang, Hodrick, Xing, and Zhang (2006; 2009) and many subsequent studies. Most papers in this literature have focused on stock return volatility; the only exception we are aware of is Huang (2009), who finds that cash-flow volatility is negatively related to stock returns. By contrast, we document a pervasive relation between fundamental volatility — based on a broad set of financial statement variables — and stock return, and show that the FVOL-return relation is, in many ways, stronger than the IVOL effect.

Various explanations for the low-volatility anomaly have been proposed in the existing lit-

erature. They range from the effects of financial market frictions (e.g., Bali and Cakici 2008; Han and Lesmond 2011; Huang, Liu, Rhee, and Zhang 2010), investors' irrational behavior and mispricing (e.g., Bali, Cakici, and Whitelaw 2011; Stambaugh, Yu, and Yuan 2015), to risk-based hypotheses. Hou and Loh (2016) empirically evaluate many of these explanations and find that they still leave a large fraction of the IVOL-return relation unaccounted for. Among the rational, risk-based explanations, Chen and Petkova (2012) find that stocks with high idiosyncratic volatility exhibit positive exposures to innovations in average stock variance, which commands a negative premium. Babenko, Boguth, and Tserlukevich (2016) argue that positive idiosyncratic shocks reduce a firm's exposure to systematic risk. Chen, Strebulaev, Xing, and Zhang (2021) attribute the IVOL anomaly to strategic risk shifting by shareholders of distressed firms. Distinct from these explanations, we reconcile empirical findings with the asset pricing effect of a concave production function. The model yields unique predictions regarding the relation between FVOL and corporate profitability and the effect of production function concavity. These predictions are supported by the data.

Our work also joins the growing body of research on production-based asset pricing, which demonstrates that firms' fundamental characteristics serve as determinants of the risk premium in the cross-section of stock returns; see, e.g., Cochrane (1991; 1996), Zhang (2005), Li, Livdan, and Zhang (2009), Liu, Whited, and Zhang (2009), Hou, Xue, and Zhang (2015), and Hou, Mo, Xue, and Zhang (2021), among others. We show that the production-based asset pricing framework can be used to understand both the fundamental volatility effect and the idiosyncratic volatility effect on stock returns.

Lastly, a negative relation between IVOL and profitability has been noted by prior studies; e.g., Jiang, Yao, and Xu (2009). However, the underlying reason for such a relation remains unknown. Hou, Xue, and Zhang (2015) and Fama and French (2016) find that the q-factor model and the five-factor model, respectively, can explain a substantial portion of the IVOL anomaly. Yet they do not offer a rationale for such findings. We find a negative relation between FVOL and profitability and show that it arises from decreasing marginal output combined with volatile production inputs. By uncovering this intrinsic link between volatility

and profitability, we identify the channel through which these multi-factor models may help explain the volatility anomaly.

The remainder of the paper is organized as follows. Section II provides a production-based asset pricing model that relates fundamental volatility to expected profitability and stock return. Section III introduces the data and measures of fundamental volatility. Sections IV and V provide the main empirical results. Section VI concludes.

2 A Model of Fundamental Volatility, Profitability, and Stock Return

2.1 Basic Idea

Firms typically operate with declining marginal productivity of resources or inputs. More concretely, when firms face constraints on certain resources, the productivity of other inputs used in production exhibits diminishing marginal returns. For example, if a firm wishes to increase output but cannot install new equipment in time, it may resort to using more labor as a substitute. However, the marginal labor productivity would decline.

Among many possible ways to model this effect, a concave production function offers perhaps the most intuitive illustration. Consider a constant-return-to-scale Cobb-Douglas production function:

$$F = XK^{1-\alpha}N^\alpha \quad (1)$$

where F is output and K and N are two types of inputs or resources. X is a productivity parameter. If $0 < \alpha < 1$ (or $\alpha(\alpha - 1) < 0$), the production function is concave in both K and N . For example, for a given K , the first- and second-order derivatives of F with respect to N are:

$$\frac{\partial F}{\partial N} = \alpha XK^{1-\alpha}N^{\alpha-1} > 0 \quad (2)$$

$$\frac{\partial^2 F}{\partial N^2} = \alpha(\alpha - 1)XK^{1-\alpha}N^{\alpha-2} < 0 \quad (3)$$

The first derivative suggests that F is an increasing function of N , so the marginal product of N is positive. The second derivative suggests that F is concave in N , and therefore the marginal product of N declines with N if K does not change.¹

Declining marginal productivity, as captured by the concavity of the production function, has an implication for the relation between input volatility and expected output — the more volatile an input is, the lower the expected output. To see this, keep X and K constant. The second-order Taylor expansion of the production function $F(N_t)$ around the expected value of N (denoted as $\bar{N}$ below) is:

$$E(F(N_t)) \approx F(\bar{N}) + \frac{1}{2} \frac{\partial^2 F(\bar{N})}{\partial N^2} \sigma^2 \quad (4)$$

where σ is the volatility of N . Since $\frac{\partial^2 F(\bar{N})}{\partial N^2} < 0$, $E(F(N_t))$ decreases with σ . Note that while the Taylor expansion delivers an approximate result, the later part of this section uses mean-preserving spread to illustrate the negative impact of fundamental volatility more rigorously.

The marginal product of K is $\frac{\partial F}{\partial K} = (1 - \alpha)XK^{-\alpha}N^\alpha$. It is often referred to as the marginal return on capital or marginal profitability (ignoring allocated accounting costs such as depreciation). Since $\frac{\partial F}{\partial K}$ is also a concave in N , the expected marginal profitability is likewise negatively related to the volatility of N .

Below, using a simple production-based asset pricing model, we demonstrate that the concavity of the production function has an asset pricing implication: under optimal production and investment decisions, volatility in a firm's fundamentals is negatively related to the expected stock return.

¹Change in marginal output is conceptually different from economies of scale. The latter has to do with how output changes when both inputs K and N change at the same rate. The production function in this example exhibits both decreasing marginal output and constant return to scale.

2.2 Model Setup

Assume that a firm's time- t production depends on two inputs: a relatively stable input K_t and a more flexible input N_t . The stability of K_t may be due to time-to-build, adjustment costs, or simply supply constraints. One may think of K as physical capital, but it could represent production technology or constrained resources. N could be raw materials, energy, labor, working capital, or other flexible resources. It is important to note that this mapping is not absolute. For example, a firm might face low adjustment costs for physical capital but severe constraints on raw material supply. In this case, the inflexible input K would be raw materials while the volatile input N would be physical capital.

The evolution of K_t follows:

$$K_{t+1} = (1 - \delta)K_t + I_t \quad (5)$$

where δ is a physical depreciation rate and I_t is time- t physical investment. This assumption implies that physical investment takes one period to become productive. Therefore, facing a positive demand shock at time t , the firm cannot increase K_t quickly enough to expand time- t production, and must instead adjust N_t . In addition, adjustment to K is subject to a convex cost Φ of the form:

$$\Phi_t = \frac{a}{2} \left(\frac{I_t}{K_t} \right)^2 K_t \quad (6)$$

Without loss of generality, assume that the other input N_t has no adjustment cost and can be used in production immediately after it is acquired. The unit price for N_t relative to the unit price of the output is W_t .

The firm's time- t net production output follows the Cobb-Douglas function with constant returns to scale:

$$F_t = X_t K_t^{1-\alpha} N_t^\alpha - W_t N_t \quad (7)$$

with $0 < \alpha < 1$. X_t represents a stochastic productivity factor. In this model, it is also the marginal (and average) profitability of capital K_t . The firm's time- t net cash flow Y_t equal

the net production output F_t minus investment I_t and adjustment costs Φ_t :

$$Y_t = F_t - I_t - \Phi_t = X_t K_t^{1-\alpha} N_t^\alpha - W_t N_t - I_t - \Phi_t \quad (8)$$

Let m_{t+k} be the one-period stochastic discount factor for period $t+k$. The cumulative stochastic discount factor is $M_{t+k} = \prod_{\tau=1}^k m_{t+\tau}$, with $M_{t+1} = M_t m_{t+1}$. The firm's objective is to maximize time- t firm value, defined as the present value of future cash flows:

$$V_t = \max \left[Y_t + E_t \left(\sum_{\tau=1}^{\infty} M_{t+\tau} Y_{t+\tau} \right) \right] \quad (9)$$

subject to the capital budget constraint in Eq. (5). Denote the firm value by $V_t = V_t(K_t, X_t)$. The firm's objective can be recursively expressed as:

$$V_t(K_t, X_t) = \max_{I_t, N_t} [Y_t + E_t(m_{t+1} V_{t+1}(K_{t+1}, X_{t+1}))] \quad (10)$$

2.3 Optimal Decisions on N_t and I_t

The decision for N_t only affects Y_t and does not affect V_{t+1} . Moreover, N_t enters Y_t only through F_t . Therefore, the optimal N_t can be solved in a static manner:

$$N_t^* = \arg \max_{N_t} [Y_t] = \arg \max_{N_t} [F_t] = \arg \max_{N_t} [X_t K_t^{1-\alpha} N_t^\alpha - W_t N_t] \quad (11)$$

Based on the first-order condition, the optimal N_t is:

$$N_t^* = K_t \left(\frac{\alpha X_t}{W_t} \right)^{\frac{1}{1-\alpha}} \quad (12)$$

Define $n_t = N_t^*/K_t = (\alpha X_t/W_t)^{1/(1-\alpha)}$. This implies $W_t = \alpha X_t n_t^{\alpha-1}$. Substituting this expression for W_t into Eq. (7) yields:

$$F_t = X_t K_t^{1-\alpha} (K_t n_t)^\alpha - \alpha X_t K_t^{1-\alpha} (K_t n_t)^{\alpha-1} K_t n_t = X_t K_t n_t^\alpha (1 - \alpha) = X_t^* K_t \quad (13)$$

where $X_t^* = (1 - \alpha)X_t n_t^\alpha$.

We now derive the condition for optimal investment I_t . Given the optimal N_t^* in Eq (12) and the reformulated expression for F_t in (13), the firm's objective function Eq. (10) becomes:

$$V_t(K_t, X_t^*) = \max_{I_t} [X_t^* K_t - I_t - \Phi_t + E_t(m_{t+1} V_{t+1}(K_{t+1}, X_{t+1}^*))] \quad (14)$$

This first-order condition on investment, $\frac{\partial V_t}{\partial I_t} = 0$, leads to:

$$1 + \frac{\partial \Phi(I_t, K_t)}{\partial I_t} = E_t(m_{t+1} \frac{\partial V_{t+1}}{\partial K_{t+1}}) \quad (15)$$

where $\frac{\partial \Phi_t}{\partial I_t} = a \frac{I_t}{K_t}$. Eq. (15) indicates that the firm invests until the marginal cost of investment (left-hand-side) equals the marginal benefit (right-hand-side). The marginal q is defined as

$$q_t = 1 + \frac{\partial \Phi(I_t, K_t)}{\partial I_t} = E_t(m_{t+1} \frac{\partial V_{t+1}}{\partial K_{t+1}}) \quad (16)$$

2.4 Effect of Fundamental Volatility on Profitability and Stock Return

The optimization problem in Eq. (14) under constant returns to scale has a well-known result: the investment return and (unlevered) stock return are the same (e.g., Hayashi, 1982; Hou, Mo, Xue, and Zhang, 2021). We state the result below and refer the readers to the existing literature for a detailed proof.

$$R_{t+1}^S = R_{t+1}^I = \frac{\frac{\partial F_{t+1}}{\partial K_{t+1}} - \frac{\partial \Phi_{t+1}}{\partial K_{t+1}} + (1 - \delta)q_{t+1}}{q_t} \quad (17)$$

where R_{t+1}^S and R_{t+1}^I denote stock return and investment return, respectively. We also know that in this model, the marginal profitability of capital, $\partial F_{t+1}/\partial K_{t+1}$, equals the average profitability, F_{t+1}/K_{t+1} :

$$\frac{\partial F_{t+1}}{\partial K_{t+1}} = X_{t+1}^* = \frac{F_{t+1}}{K_{t+1}} \quad (18)$$

Therefore the expected stock return is:

$$E_t(R_{t+1}^S) = \frac{E_t(X_{t+1}^*) - E_t(\frac{\partial \Phi_{t+1}}{\partial K_{t+1}}) + (1 - \delta)E_t(q_{t+1})}{q_t} \quad (19)$$

In this expression, the first component of the numerator, $E(X_{t+1}^*)$, represents the expected profitability. Thus, all else equal, the expected stock return is positively related to expected profitability. However, in general, $E_t(R_{t+1}^S)$ also affects the other two components in the numerator: $-E_t(\frac{\partial \Phi_{t+1}}{\partial K_{t+1}})$ and $(1 - \delta)E_t(q_{t+1})$.²

Below, in three steps, we show that in this model the volatility of input N_{t+1} has a negative impact on expected profitability $E(X_{t+1}^*)$ and expected stock return $E(R_{t+1}^S)$.

Step 1. The following proposition states that under fairly general conditions on X_t^* and m_t , stock return R_{t+1}^S is increasing and weakly concave function of profitability X_{t+1}^* .

Proposition 1. If for all $\tau \geq t$, 1) $\partial X_{\tau+1}^*/\partial X_\tau^* \geq 0$ and 2) $\partial m_{\tau+1}/\partial X_\tau^* \leq 0$, then the stock return R_{t+1}^S is a strictly increasing and weakly concave function of profitability X_{t+1}^* . That is,

$$\frac{\partial R_{t+1}^S}{\partial X_{t+1}^*} > 0 \quad (20)$$

$$\frac{\partial^2 R_{t+1}^S}{\partial (X_{t+1}^*)^2} \leq 0 \quad (21)$$

The proof is provided in Appendix A.1. Note that both conditions 1) and 2) are supported by commonly used asset pricing assumptions. For instance, suppose profitability follows an AR(1) process:

$$X_{t+1}^* = c_0 + c_1 X_t^* + e_{t+1}$$

If $0 \leq c_1 < 1$, then $\partial X_\tau^*/\partial X_{\tau-1}^* = c_1 \geq 0$, satisfying Condition 1).

²Existing studies mainly rely the first term to motivate the relation between profitability and return. In more general settings—for example, with heterogeneous or time-varying capital adjustment costs—other components of the expected return are determined by factors possibly distinct from profitability. In particular, q_t and q_{t+1} are considered proxies for current and expected capital investments; see, for example, Hou, Mo, Xue, and Zhang (2021).

It is also common to assume a stochastic discount factor of the form:

$$m_{t+1} = a - b\Psi_{t+1}, \quad b > 0$$

where Ψ_{t+1} represents systematic risk factors such as aggregate consumption growth and market return. If X_{t+1}^* is positively correlated with Ψ_{t+1} , then under the AR(1) process for X^* , we have $\partial m_{t+1}/\partial X_t^* \leq 0$, satisfying Condition 2).

Step 2. Note that profitability X_{t+1}^* is an increasing and strictly concave function of input N_{t+1}^* . From Eq (13), $X_{t+1}^* = (1 - \alpha)X_{t+1}K_{t+1}^{-\alpha}(N_{t+1}^*)^\alpha$, we obtain

$$\frac{\partial X_{t+1}^*}{\partial N_{t+1}^*} = (1 - \alpha)\alpha X_{t+1}K_{t+1}^{-\alpha}(N_{t+1}^*)^{\alpha-1} > 0 \quad (22)$$

$$\frac{\partial^2 X_{t+1}^*}{\partial (N_{t+1}^*)^2} = -\alpha(1 - \alpha)^2 X_{t+1}K_{t+1}^{-\alpha}(N_{t+1}^*)^{\alpha-2} < 0 \quad (23)$$

Step 3. Combining Proposition 1 with Eqs. (22) and (23), we conclude that stock return R_{t+1}^S is a strictly increasing and strictly concave function of N_{t+1}^* :

$$\frac{\partial R_{t+1}^S}{\partial (N_{t+1}^*)} > 0 \quad (24)$$

$$\frac{\partial^2 R_{t+1}^S}{\partial (N_{t+1}^*)^2} < 0 \quad (25)$$

Combining the concavity of stock return expression in (25) with the Taylor expansion argument in (4), we can infer that fundamental volatility, $\text{Var}(N_{t+1}^*)$, has a negative impact on the expected stock return. Note that the Taylor expansion is approximate. To quantify the effect more rigorously, below we define an increase in fundamental volatility that is consistent with a mean-preserving spread (e.g., Rothschild and Stiglitz, 1970).

Let $\tilde{N} = N^* + e$. e is a zero-mean random variable with standard deviation σ_e and independent of N^* . $\tilde{N}$ represents a mean-preserving spread of N^* because adding e increases variance without changing the mean.³ The increase in variance, $\sigma_e^2 = \text{Var}(\tilde{N}) - \text{Var}(N^*)$, is

³Note that adding e to N^* is an intuitive way, but not the only way, to generate a mean-preserving spread.

referred to as a *mean-preserving increase* in variance.

It is well established (e.g., Rothschild and Stiglitz, 1970) that the expected value of a concave function of a random variable decreases under a mean-preserving spread (or equivalently, a mean-preserving increase in variance). Since the proof is straightforward, we state the result directly in the following theorem.

Theorem 1. Given the model setup in Section 2.2 and the two conditions in Proposition 1, a *mean-preserving increase* in $\text{Var}(N^*)$ reduces both expected profitability $E(X_{t+1}^*)$ and expected stock return $E(R_{t+1}^S)$.

Finally, because stock return R_{t+1}^S is a monotonically increasing function of profitability X_{t+1}^* , there is a positive and monotonic relation between the variance of these two variables, $\text{Var}(X_{t+1}^*)$ and $\text{Var}(R_{t+1}^S)$. Together with Theorem 1, this monotonic relation leads to the following result regarding the effect of stock return volatility:

Corollary 1. Given the model setup in Section 2.2 and the two conditions in Proposition 1, a *mean-preserving increase* in stock return variance $\text{Var}(R_{t+1}^S)$ reduces both expected profitability $E(X_{t+1}^*)$ and expected stock return $E(R_{t+1}^S)$.

Thus, higher return volatility leads to lower profitability and lower expected return. This provides an explanation to the idiosyncratic volatility anomaly documented by Ang et al. (2006, 2009) and suggests that the fundamental volatility effect and the IVOL anomaly are closely related.

3 Data and Measures of Fundamental Volatility

3.1 Data and Sample

The data on stock returns and the accounting data are from CRSP and Compustat, respectively. The sample includes non-financial common stocks (CRSP share codes 10 and 11) listed on the NYSE, Amex, or NASDAQ. Financial firms (SIC codes 6000-6999) are excluded due to their unique accounting characteristics. As described below, the fundamental volatility measures involve 12 consecutive quarters of accounting data. The analysis also requires a minimum of 500 firms in the cross section for any given quarter. Given these sample selection criteria, the sample period in this study spans from 1976Q4 to 2024.

Additionally, this study uses the Fama-French factors and the industry classifications from Ken French’s data library, as well as the q-factors from the Global-q website.⁴

3.2 FVOL Measures

The accounting measures of production inputs are identified from the quarterly balance sheet and quarterly income statement. Among all major accounting variables in Compustat, we select items related to operation inputs according to the following criteria. 1) We exclude financial investments (e.g., Cash and Short-term Investments), tax-related items (e.g., Income Taxes), and “Other” variables (e.g., Other Current Assets and Other Current Liabilities). 2) We exclude items with insufficient observations in the cross-section—specifically, those with fewer than 500 observations per quarter during our sample period (e.g., Preferred stock and Non-controlling Interest). 3) We exclude sales- and profit-related income-statement items, as they measure outputs rather than inputs. 4) We keep financing variables, i.e., items related to liabilities and equity, as long as they are not excluded by the above criteria. Financing is considered a form of input, and financing frictions affect firms’ investment and operation decisions. Several existing studies explicitly include financing costs or constraints

⁴The websites are https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html and <https://global-q.org/factors.html>, respectively.

in the production-based asset pricing framework, to the effect that equity profitability is a concave function of financing; see, e.g., Li, Livdan, and Zhang (2009) and Livdan, Sapriz, and Zhang (2009). Li and Zhang (2010) further show that the negative effect of investment on stock returns is stronger among firms facing tighter financing constraints. Nevertheless, we note that all the key results remain robust when financing items are excluded from the FVOL measures. 5) Finally, we exclude two variables that have correlations above 0.99 with already-included variables: Common equity (highly correlated with Stockholders' Equity), and Liabilities and Stockholders' Equity (redundant to Total Assets).

This procedure results in 14 selected accounting items, 11 from the balance sheet and 3 from the income statement. They are listed in the table below, with the corresponding Compustat variable names in the parentheses. Appendix A.2 provides a complete list of major accounting items in Compustat, and the reasons for items excluded from the FVOL measures.

Accounting Variables For Fundamental Volatility Measures	
From Balance Sheet (11 items)	
Assets (5 items)	Liabilities and Equity (6 items)
Current Assets-Total (actq)	Current Liabilities-Total (lctq)
Receivables-Total (rectq)	Debt in Current Liabilities (dlcq)
Inventories-Total (invtq)	Accounts Payable (apq)
Property, plant and equipment, net (ppentq)	Long-term Liabilities-Total (dlttq)
Assets-Total (atq)	Liabilities-Total (ltq)
	Stockholders Equity (seqq)
From Income Statement (3 items)	
Operating Expense (xoprq)	
Cost of Goods Sold (cogsq)	
Selling, General and Administrative Expenses (xsqaq)	

Let $Z_{k,\tau}$ denote an accounting variable ($k=1$ to 14) for quarter τ . To remove persistence and seasonality, we take the four-quarter difference of an accounting variable, $\Delta_{k\tau} = Z_{k,\tau} -$

$Z_{k,\tau-4}$. The individual fundamental volatility measure for quarter t , $FVOL_{kt}$, is the standard deviation of $\Delta_{k\tau}$ divided by the average of total sales:⁵

$$FVOL_{kt} = \frac{\text{Std}(\Delta_{k\tau})}{\text{Average}(\text{Sales}_\tau)} \quad (26)$$

Both the standard deviation of $\Delta_{k\tau}$ and the average of sales are computed over 8 rolling fiscal quarters for which the financial statements are publicly available by the end of quarter t . We assume that a quarterly financial statement is public available at the end of the quarter of the earnings announcement date (variable rdq in Compustat).⁶ We require the existence of $\Delta_{k\tau}$ and sales in at least 4 out of 8 quarters for a firm-quarter measure $FVOL_{kt}$ to be valid.

Based on the 14 individual fundamental volatility measures, we further construct an average FVOL measure to summarize the common information across them. For each of the 14 measures, we first compute the percentile ranks across all stocks in a given quarter. Then, for a given stock in a given quarter, we take the average of the 14 percentile ranks. This average rank measure is denoted $FVOL_A$. We require a stock to have nonmissing observations for at least 10 of the 14 $FVOL_k$ measures in a given quarter for $FVOL_A$ to be valid.

3.3 Descriptive Statistics

Table 1 presents summary statistics for the 14 individual $FVOL_k$ measures as well as the average FVOL. The distributional statistics are computed cross-sectionally within each quarter and then averaged over quarters. As shown in Panel A, on average, there are about 1,900 firms in each quarter. The 14 $FVOL_k$ measures are quite different in their cross-sectional means and standard deviations. Controlling for such heterogeneity is a key reason why the

⁵The key results of this paper are robust to several variations in the FVOL measures, such as using $\text{Std}(Z_{K,\tau})$ as the numerator, using average total assets as the denominator, or measuring FVOL as the standard deviation of the ratio $\Delta_{k,\tau}/\text{Sales}_\tau$ or $\Delta_{k,\tau}/\text{Assets}_\tau$.

⁶Full financial statements may be available with a delay after the earnings announcement date rdq , especially in the early sample period. Therefore $FVOL_{kt}$ constructed using our procedure may not strictly be available publicly at the end of quarter t . This concern is mitigated by the fact that $FVOL_{kt}$ has power to predict returns for many quarters after quarter t .

average FVOL is based on the cross-sectional ranks of $FVOL_k$ instead of their raw values.

Panel B of the table reports the Spearman rank correlations among the 14 $FVOL_k$ measures as well as their correlations with the average FVOL. These correlations are computed across stocks in a given quarter and then averaged over time. As the panel shows, the 14 FVOL measures exhibit high levels of correlations, suggesting a strong common component. The rank correlations between $FVOL_A$ and individual $FVOL_k$ range from 0.54 to 0.87.

4 Empirical Results

In this section, we empirically investigate the effect of FVOL on stock returns and profitability. The model in Section 2 suggests that the volatility of time- $t + 1$ operating inputs is negatively related to the expected profitability and expected stock return at time $t + 1$, conditional on information available at time t . In the data, fundamental volatility is persistent over time. Thus, the contemporaneous relation suggested by the model translates into a predictive relation between fundamental volatility measured at quarter t with profitability and stock returns during the subsequent quarters ($t + 1$, $t + 2$, etc). Our analysis focuses on this predictive effect.

4.1 The FVOL-Return Relation

We start with a portfolio analysis to illustrate the FVOL-return relation. At the end of each calendar quarter, we form value-weighted decile portfolios based on each of the 14 individual $FVOL_k$ measures as well as on the average FVOL. To mitigate the effect of market microstructure noise on stock returns, we exclude stocks priced below \$5 at the time of portfolio formation. The portfolios are then held over the subsequent 8 quarters and rebalanced monthly to maintain value weighting. When computing holding-period stock returns, we incorporate CRSP delisting returns following Shumway (1997). If the delisting return is missing in CRSP, we assign a delisting return of -30% for performance-related delisting and 0 otherwise.

Based on monthly portfolio returns, we further compute portfolio alphas using five different factor models. They include CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama-French (2015) five-factor model, and the q-factor model of Hou, Xue, and Zhang (2015).

Table 2 reports the portfolio performance for the holding quarter immediately after portfolio formation (i.e., Q1). For brevity, we only report the average monthly returns and monthly alphas for the value-weighted long-short portfolios (the Low-High portfolios hereafter). These portfolios take long positions in stocks of the bottom $FVOL_k$ decile and short positions in stocks of the top decile. See Appendix A3 for additional results.

Based on the individual $FVOL_k$ measures, most of the returns and alphas of these Low-High portfolios are significantly positive, suggesting a pervasive effect of fundamental volatility on stock returns. Out of 84 observations (14 $FVOL_k$ measures and 6 performance measures), only 7 cases have t-statistics below 1.64. Notably, these insignificant cases are concentrated under the two factor models that include a profitability factor—the Fama-French (2015) five-factor model and the Hou et. al. (2015) q-factor model—consistent with a link between profitability and the $FVOL$ effect.⁷

Based on the averaged $FVOL_A$, the Low-High portfolio earns an average monthly return of 0.93% (t=4.09), CAPM alpha of 1.25% (t=5.89), three-factor alpha of 1.21% (t=6.21), four-factor alpha of 1.15% (t=5.85), five-factor alpha of 0.73% (t=4.10), and q-factor alpha of 0.67% (t=3.45). These t-statistics are well above the multiple-testing threshold suggested by Harvey, Liu, and Zhou (2016) (i.e., $t > 3.0$). The results suggest that $FVOL_A$ captures a substantial common effect of the 14 $FVOL$ measures on stock returns.

The long-horizon predictive power of $FVOL$ is reported in Table 3, where the holding period goes from 1 quarter in Table 2 to each of the 8 quarters (Q1 to Q8) after portfolio formation. For brevity, we only report the results based on $FVOL_A$. The table demonstrates the highly persistent effect of $FVOL$ on stock returns. The Low-High portfolio returns

⁷Specifically, the insignificant cases include the CAPM alpha of the $FVOL$ portfolio based on $dlcq$ (debt in current liabilities), the five-factor alphas and the q-factor alphas of the $FVOL$ portfolios based on $actq$ (accounts assets), $seqq$ (stockholders' equity), and $xsgaq$ (selling, general, and administrative expenses).

and alphas are significantly positive throughout the 8 quarters. By quarter 8, the average monthly return remains substantial at 0.70%, with alphas ranging from 0.64% to 0.96%, all statistically significant. Averaged over the 6 performance measures, the predictive power of $FVOL_A$ in the 8th quarter remains above 80 percent of that in the first quarter after formation.

The last row of this table, labeled “JT8”, summarizes the portfolio performance over 8 quarters using the Jegadeesh and Titman (1993) non-overlapping portfolio approach. Specifically, since we hold the portfolios over 8 quarters, in each quarter τ there are 8 portfolios with the same $FVOL_A$ decile rank but formed during each of the previous 8 quarters ($\tau - 1$, $\tau - 2$, ..., $\tau - 8$). We average the monthly returns during quarter- τ of these 8 portfolios with the same decile rank to obtain a single time series of monthly returns, which is then used to compute the alphas. The average return to the Low-High “JT8” portfolio is 0.81% ($t=4.04$) per month. The alphas for the portfolio are 1.11% ($t=6.03$), 1.08% ($t=6.41$), 1.02% ($t=5.96$), 0.70% ($t=4.42$), and 0.65% ($t=3.82$) under CAPM, the three-factor, four-factor, five-factor, and q-factor models respectively. These results confirm the long-horizon predictive power of $FVOL_A$ on stock returns.

While Tables 2 and 3 report the results for the Low-High portfolios only, Figure 1 provides a more complete picture of the performance of the 10 $FVOL$ decile portfolios. In the plot, performance is measured by the alpha of a representative factor model — the Carhart (1994) four-factor model. The left panel shows that the portfolio alpha declines with the $FVOL_A$ decile ranks during the quarter immediately after portfolio formation, and the right panel shows a similar declining pattern for the “JT8” portfolios, confirming the negative $FVOL$ -alpha relation over a long horizon.

4.2 Comparing with the IVOL Effect

Since the negative $FVOL$ -return relation resembles the IVOL anomaly, there is an interest in understanding how distinct the two effects are. We highlight several distinctions here.

First, note that the IVOL anomaly is in the form of extremely low returns and negative

alphas to stocks with high IVOL, whereas stocks with low IVOL tend to have insignificant alphas (e.g., Ang et al., 2006). As demonstrated in the Appendix A3, the FVOL effect is different. Table A2 in the appendix shows that during the quarter immediately after portfolio formation, over the 14 individual $FVOL_k$ measures as well as for $FVOL_A$, stocks in the bottom FVOL decile tend to have significantly positive alphas under various factor models, while stocks in the top decile have significantly negative alphas. Table A3 in the appendix shows a similar pattern over the long horizon of 8 quarters. Therefore, both low-FVOL and high-FVOL stocks have significant alphas, but with opposite signs.

Another well-known feature of the IVOL anomaly is that high- and low-IVOL stocks differ dramatically in size. For example, according to Ang et al. (2006), stocks in the bottom IVOL quintile account for 53% of total market value, while stocks in the top quintile account for only 1.9%. In our sample, which excludes financial firms and stocks priced below \$5, stocks in the bottom IVOL decile account for over 25% of total market value while stocks in the top IVOL decile account for less than 2%. In Figure 2, we plot the average shares of the entire market value for the 10 $FVOL_A$ deciles. $FVOL_A$ is also negatively related to size, but in a much more modest way. The market-value share of stocks in the bottom $FVOL_A$ decile is 16.3%, compared with 5.2% for stocks in the top decile.

The return-predictive horizon is another dimension in which the FVOL and IVOL effects are different. IVOL predicts stock returns mainly during the first one or two quarters (e.g., Poon et al., 2022). By contrast, as shown in Table 3, the return-predictive power of FVOL lasts for at least 8 quarters after portfolio formation.

A further distinction is in the alphas associated with FVOL and IVOL. Hou, Xue, and Zhang (2015) and Fama and French (2016) report that the IVOL anomaly is largely explained by the q-factor model and the five-factor model. By contrast, as Tables 2 and 3 indicate, the FVOL portfolios exhibit significant alphas under these two factor models.

Finally, we use double-sorted portfolios to assess to what extent the FVOL effect is explained by the IVOL effect, and vice versa. In each quarter, we sort stocks independently by $FVOL_A$ and IVOL into quintiles, resulting in 25 (5×5) value-weighted portfolios. IVOL

is the standard deviation of residuals from the Fama-French three-factor model, estimated using daily returns during the ranking quarter. The portfolios are held for each of the subsequent 8 quarters. To measure the effect of FVOL while controlling for IVOL, we average the performance of portfolios with the same FVOL quintile rank but with different IVOL quintile ranks.

Panel A of Table 4 confirms the negative unconditional FVOL-return relation using univariate quintile portfolios. In Panel B, we report the FVOL-return relation after controlling for IVOL using the above-described double-sorting approach. The panel shows that the negative effect of FVOL on stock return remains highly significant after controlling for IVOL, both during the first quarter after portfolio ranking (Q1) and during the 8 quarters after ranking (JT8). In fact, during the subsequent 8 quarters, the returns and alphas of the FVOL portfolios become even higher, with stronger statistical significance, after controlling for IVOL, relative to the corresponding unconditional performance reported in Panel A.

For comparison, Panel C of the table reports the unconditional performance of the IVOL quintile portfolios. In Q1, the Low-High IVOL portfolio generates a monthly return of 0.58% with a marginally significant t-statistic. The alphas are significant under CAPM, the three-factor and four-factor models, but become insignificant under the five-factor and the q-factor models. These patterns are well documented in the existing literature (e.g., Fama and French 2016; Hou, Xue and Zhang 2015). Over the 8-quarter horizon, the portfolio return becomes insignificant, while the alphas under CAPM and the three-factor and four-factor models remain significant. Poon et al. (2022) attribute this to the correlation between IVOL and beta, reflecting a betting-against-beta effect. Nonetheless, the alphas under the five-factor and q-factor models remain insignificant over the long horizon.

Panel D further reports the performance of Low-High IVOL portfolios after controlling for FVOL, using a similar double-sorting procedure as in Panel B. In this panel, the return to the IVOL portfolio becomes insignificant during Q1. The alphas under CAPM, the three-factor and four-factor models remain significant, albeit with reduced magnitude relative to Panel C. Over the 8 quarters, the CAPM alpha and the three-factor alpha remain significant,

but again with reduced magnitude relative to Panel C.

Overall, we infer from Table 4 that controlling for IVOL does not materially affect the FVOL-return relation. However, controlling for FVOL weakens the IVOL-return relation.⁸

4.3 Explaining the FVOL Effect on Stock Returns

We now turn to the potential channels through which FVOL predicts stock returns. Our model suggests a profitability channel, whereby FVOL negatively affects stock returns by reducing expected profitability. We empirically investigate this prediction against a set of competing hypotheses.

4.3.1 The FVOL-Profitability Relation

We consider three profitability measures from existing literature: gross profitability as per Novy-Marx (2013), operating profitability following Fama and French (2015), and return on equity by Hou, Xue, and Zhang (2015). All three measures are constructed using Compustat quarterly data. Gross profitability is revenues minus cost of goods sold, deflated by lagged total assets (Compustat items `revtq`, `cogsq` and `atq`). Operating profitability is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense (Compustat items `revtq`, `cogsq`, `xsgaq`, and `xintq`), and then divided by lagged book value of equity (BE). Return on equity is income before extraordinary items (Compustat item `ibq`) deflated by BE. BE is the stockholders' equity, plus balance-sheet deferred taxes and investment tax credit (Compustat items `seqq` and `txditcq`), minus the book value of preferred stocks. We set the book value of preferred stocks to their redemption, or par value (Compustat items `pstkrq` and `pstkq`), depending on availability.

In Figure 3, we illustrate the FVOL-profitability relation using a sorted portfolio approach. Panels A, B, and C plot, respectively, the averages of Gross Profitability, Operating Profitability, and Return On Equity, for each of the FVOL_A deciles. Each panel shows the

⁸The table suggests that FVOL and IVOL has relatively distinct return predictive information at the short horizon (Q1). However, as we show subsequently, their relation with stock returns are both explained by the contemporaneous profitability channel, suggesting that these two phenomena share the same origin.

results for the immediate next quarter (left side) and for the next 8 quarters using the “JT8” approach (right side). The figure reveals a strong and monotonic negative relation between $FVOL_A$ and subsequent profitability.

In Table 5 we further show that $FVOL_A$ is a robust predictor of profitability using multivariate Fama-MacBeth regressions. The dependent variable is one of the three profitability measures during each of the 8 quarters (Q1 to Q8) after the initial measurement of $FVOL_A$. The key explanatory variable of interest is $FVOL_A$. The control variables include a large number of lagged firm characteristics. The first control variable is past profitability (PP), based on the same profitability measure as the dependent variable. Other controls include Idiosyncratic Volatility (IVOL), Book-to-Market (BM), Market Capitalization (SIZE), Negative Profitability (NP), Negative Accruals (-ACCBE), Positive Accruals (+ACCBE), Asset Growth (AG), No Dividends (NODIV), Dividends-to-Book (DIVBE), Returns in year $y-1$ (RET_1yr), Returns in year $y-3$ to $y-2$ (RET_23yr), Probability of Default on Debt (O_Score), and Composite Index of Firm Strength (F_Score). These variables are used by existing studies, e.g., Fama and French (2006) and Jiang et al. (2009), as predictors of profitability. Detailed definitions are provided in Appendix A.4. All explanatory variables, except $FVOL_A$, are winsorized at the 1st and 99th percentile and then cross-sectionally standardized in each quarter to have zero means and unit standard deviations.

Table 5 shows that the predictive power of $FVOL_A$ on all three profitability measures persists over the subsequent 8 quarters. Columns labeled with odd numbers (1, 3, ..., 15) report the univariate regressions without control variables. Columns labeled with even numbers (2, 4, ..., 16) report multivariate regressions with controls. Since profitability measures are serially correlated, the t-statistics in this table are based on Newey-West standard errors with a 12-quarter lag.

Since the results are similar across the three profitability measures, we summarize them based on return on equity in Panel C. In univariate regressions, the coefficients on $FVOL_A$ are around -0.10% across the 8 quarters, all significantly negative. In multivariate regressions, the coefficients on $FVOL_A$ are reduced to approximately -0.03%, but statistical significance

remains very high. The coefficients suggest that one percentile increase in $FVOL_A$ reduces return on equity by 0.03%.

Also note that the coefficients on past profitability are positive with very high statistical significance. Yet $FVOL_A$ has information about future profitability beyond past profitability. This suggests that profitability does not follow a simple AR(1) process, but is possibly driven by multiple components, each with its own dynamics. Finally, many other control variables have significant coefficients. Nonetheless, the predictive power of $FVOL_A$ is not fully subsumed by these controls.

4.3.2 Explaining the FVOL-Return Relation

We now use Fama-MacBeth regressions to examine the channels through which FVOL predicts returns. The primary channel of interest, as predicted by our model, is the effect of FVOL on profitability, which we refer to as the contemporaneous profitability channel. In addition, we explore whether hypotheses proposed in the existing literature for the low-risk anomaly can explain the FVOL effect. A prominent explanation for the low-risk anomaly is that investors' lottery preferences lead to overpricing of stocks with high return skewness (e.g., Barberis and Huang, 2008; Kumar, 2009; Bali et al., 2011; Han and Kumar, 2013; and Bali, Brown, and Tang, 2017). Another hypothesis emphasizes market frictions and attributes the low-risk anomaly to market microstructure effects (e.g., Fu, 2009; Huang et al., 2009). Besides these explanations, earnings shocks and exposure to innovation in average stock variance have been linked to the idiosyncratic volatility effect (e.g., Jiang et al., 2009; Chen and Petkova, 2012).

In the baseline regression analysis, the dependent variable is the monthly stock return during each of the subsequent 8 quarters following the measurement of $FVOL_A$. The key explanatory variable is $FVOL_A$. Variables used to explain the FVOL-return relation are added as control variables. The main control variables of interest, following our model, are the three profitability measures contemporaneous with the stock returns. That is, if the dependent variable is stock return during the k -th quarter after FVOL measurement, the

profitability measure is the one observed during that same quarter.

Motivated by the alternative hypotheses discussed above, we further include a broad set of additional control variables. They include return skewness (Skew), coskewness (Coskew), one-month reversal (Lagret), Maximum daily return (Maxret), days of zero returns (Zeroret), average variance beta (AvgVar β), Amihud illiquidity ratio (Illiq), standardized unexpected earnings (SUE), and accruals (Acc). We further include firm size (Size), book-to-market ratio (BM), operating profitability (OP), and asset growth rate (AG) as controls. These variables are all measured during the FVOL measurement quarter. Detailed definitions are provided in Appendix A.5. They are all winsorized at the 1st and 99th percentile, and then standardized cross-sectionally in each quarter.

To evaluate the contribution of each control variable to the FVOL-return relation, we adopt the four-stage decomposition procedure of Hou and Loh (2016). The first stage in their approach is the monthly Fama-MacBeth regression of excess stock returns on FVOL_A:

$$R_{it} = \alpha_t + \gamma_t \text{FVOL}_{it-1} + \epsilon_{it} \quad (27)$$

In the second stage, candidate explanatory variables (i.e., control variables) are added to the first-stage regressions, to evaluate whether these variables subsume the FVOL coefficient:

$$R_{it} = \alpha_t + \beta_t \text{FVOL}_{it-1} + \sum_{j=1}^N \theta_{jt} \text{Control}_{jit-1} + \eta_{it} \quad (28)$$

The third stage estimates the relation of FVOL with the candidate explanatory variables (controls) via Fama-MacBeth regressions:

$$\text{FVOL}_{it-1} = a_t + \sum_{j=1}^N \delta_{jt-1} \text{Control}_{jit-1} + \mu_{it-1} \quad (29)$$

The fourth stage, based on Eq. (30) below, decomposes the FVOL-return relation (γ_t , defined below) into a component explained by the control variables ($\sum_{j=1}^N \gamma_{jt}^c$) and a residual component that is independent of all controls (γ_t^R). This decomposition uses the coefficients

on FVOL from stage 1 (γ_t) and the coefficients on the controls from stage 3 (δ_{jt-1}). The time-series average of $\frac{\gamma_{jt}^c}{\gamma_t}$, or $\frac{\bar{\gamma}_{jt}^c}{\gamma_t}$, measures the average fraction of the FVOL-return relation attributable to a control j . The time-series average of $\frac{\gamma_t^R}{\gamma_t}$, or $\frac{\bar{\gamma}_t^R}{\gamma_t}$, captures the average fraction of the FVOL-return relation unexplained by all controls. The average residual fraction $\frac{\bar{\gamma}_t^R}{\gamma_t}$ is our key parameter of interest in this last stage.

$$\begin{aligned}
\gamma_t &= \frac{\text{Cov}(R_{it}, \text{FVOL}_{it-1})}{\text{VAR}(\text{FVOL}_{it-1})} \\
&= \frac{\text{Cov}(R_{it}, \sum_{j=1}^N \delta_{jt-1} \text{Control}_{jit-1} + a_{t-1} + \mu_{it-1})}{\text{VAR}(\text{FVOL}_{it-1})} \\
&= \frac{\text{Cov}(R_{it}, \sum_{j=1}^N \delta_{jt-1} \text{Control}_{jit-1})}{\text{VAR}(\text{FVOL}_{it-1})} + \frac{\text{Cov}(R_{it}, (a_{t-1} + \mu_{it-1}))}{\text{VAR}(\text{FVOL}_{it-1})} \\
&= \sum_{j=1}^N \gamma_{jt}^c + \gamma_t^R
\end{aligned} \tag{30}$$

Panel A of Table 6 reports results of Fama-MacBeth regressions at the first two stages. In this panel, as an illustration, the dependent variable is the monthly stock return during the first subsequent quarter (Q1). The univariate Fama-MacBeth regression in Column (1) yields a coefficient of -0.012 ($t=-4.15$) on FVOL_A , indicating that average monthly returns decrease by 1.2 basis points when FVOL_A increases by 1 percentile. The significant coefficient on FVOL_A in Column (2) (labeled “Lagged”) further suggest that, after controlling for variables representing competing hypotheses, the FVOL-return relation persists.

In multivariate regression (3) to (5), we add to the explanatory variable list gross profitability (GP), operating profitability (OP), and return on equity (ROE), respectively. These profitability measures are contemporaneous with the dependent variable (stock return). The results show that the FVOL-profitability channel is the most important one to explain the FVOL-return relation. In regression (3), controlling for gross profitability flips the sign of the FVOL coefficient, from -0.007 to 0.004. In regression (4) and (5), the coefficient on FVOL becomes insignificant after controlling for either operating profitability or return on equity.

It is worth noting that profitability is likely related to contemporaneous stock returns

through channels other than its relation with lagged FVOL. Thus, contemporaneous profitability in the regressions is not to be interpreted as an instrumental variable (i.e., affecting stock return only through FVOL and being orthogonal to the error term). Nevertheless, if the FVOL-return relation did not go through the profitability channel at all, the coefficient on FVOL would have remained significant when profitability is controlled for.

Panel B of the table extends the regression analysis to stock returns during each of the 8 quarters (Q1 to Q8) after FVOL measurement. The results are consistent with those in Panel A. The negative FVOL-return relation disappears once we control for profitability.

Furthermore, Figure 4 plots the residual FVOL-return relation, i.e., the unexplained fraction $\frac{\gamma_t^R}{\gamma_t}$, during each of the 8 quarters (Q1 to Q8) after FVOL measurement. The lagged firm characteristics from competing hypotheses (“Lagged” in the plot) collectively explain about half of the FVOL-return relation, as the residual fraction remains roughly 50% throughout the 8 quarters. The residual fraction flips sign after additionally controlling for gross profitability (GP), and becomes trivial after controlling for operating profitability (OP) or return on equity (ROE).

To sum up, the analyses in Table 6 and Figure 4 highlight that the FVOL-profitability channel is the most important one for explaining the FVOL-return relation. While other explanatory variables help explain the relation to some extent, they leave a large part of it unexplained.⁹

Finally, in Appendix A.6, we show that the IVOL anomaly, i.e., the negative IVOL-return relation, is also largely explained by the contemporaneous profitability channel.

5 Further Analysis

We perform three sets of additional analyses to further understand the FVOL effect. In Section 5.1, by examining the time variation of the Low-High FVOL portfolio returns, we show

⁹As a robustness check, we also use double-sorting to examine the FVOL-profitability channel in explaining the FVOL-return relation. The untabulated results show that once controlling for contemporaneous profitability, the FVOL-return relation is no longer significant. This is consistent with the regression results in Table 6.

that FVOL and the profitability factors in the existing multi-factor models likely capture the same systematic risk. In Section 5.2, we empirically verify another model prediction and show that the FVOL-return and FVOL-profitability relations are stronger among firms facing more concave production functions. In Section 5.3, we highlight the significance and uniqueness of the information content of FVOL in the context of a factor zoo—that is, after controlling for a large set of asset pricing factors from the existing literature.

5.1 Time Series Variations

Production-based asset pricing models offer an implicit risk-based interpretation, which provides a way to understand how fundamental volatility is related to systematic risk. In our model, stock return is a nonlinear function of profitability X^* . If X^* is correlated with systematic factors, then the stock beta is also a function of X^* , and therefore a function of FVOL.

Although the model does not directly identify the specific systematic risk factors, it suggests that low-FVOL stocks and high-profitability should have similar exposure to the same set of risk factors. In Panel A of Figure 5, we check this implication by plotting the time series of the Low-High FVOL_A portfolio returns together with the two profitability factors — the Robust-Minus-Weak (RMW) factor in the five-factor model and the Return On Equity (ROE) factor in the q-factor model. To highlight the slow-moving component of the returns and factors, we plot their 12-month moving averages. NBER recessions are shaded in the figure.

As shown in the plot, the FVOL portfolio returns are more volatile than the profitability factors, partly because the former is based on decile portfolios while the profitability factors are constructed using the 2×3 size-and-profitability sorted portfolios. Despite this difference, we can see that the FVOL returns and the profitability factors are highly correlated and exhibit similar counter-cyclical variation over business cycles. This provides intuitive evidence that the FVOL portfolio returns and the profitability factors share similar systematic risk exposures.

Panel B of Figure 5 plots the Low-High FVOL_A portfolio returns together with the Low-High IVOL portfolio returns. We plot IVOL returns separately because they are far more volatile than the profitability factors. The plot shows that the IVOL returns have a high correlation with the FVOL returns, and they both move counter-cyclically. This suggests that IVOL and FVOL are likely associated with similar risk exposures.

5.2 The Effect of Concave Production Functions

We now investigate another important prediction of the model — the negative effect of FVOL on profitability and stock returns is stronger when the production function is more concave.

We begin by estimating the concavity of production functions. Firms typically use a large number of operating inputs, some of which are highly correlated. To keep the specification parsimonious and alleviate the multicollinearity concerns, we estimate the log version of a Cobb-Douglas production function with two inputs — total assets (TA) and cost of goods sold (COGS). The regression model is:

$$\ln(\text{Sales}) = a + b\ln(\text{TA}) + c\ln(\text{COGS}) + e \quad (31)$$

This production function is motivated by the example used in the model (Eq. (1)), although we do not impose constant returns to scale in the regression. Following Eq (3), the concavity of the production function with respect to TA is measured by $b(1 - b)$ and the concavity with respect to COGS is measured by $c(1 - c)$. The overall concavity measure is the average of the two:

$$\text{Concavity} = \frac{b(1 - b) + c(1 - c)}{2} \quad (32)$$

The estimated firm-level concavity measure can be noisy, especially for firms with a short data history. Assuming that firms within the same industry have similar production functions, we estimate the model by pooling all firms in a given industry over the entire sample period. Further, to mitigate the influence of outliers, we winsorize quarterly data

on sales, total assets, and cost of goods sold at the top and bottom 1 percent within each industry. We follow the Fama-French 30-industry classification.

Figure 5 displays the estimated concavity measures for the 30 industries. The estimated coefficients b and c lie between 0 and 1 for all industries. As a result, all industries have concavity measures between 0 and 1, as shown in the figure. Chemicals, Healthcare, Petroleum, Personal Services, Business Equipment and Other industries have the highest concavity while Apparel, Construction, Food Products, Paper, Tobacco, and Utilities industries have the lowest.

Figure 6 illustrates the effect of concavity on the FVOL-return relation using sorted portfolios. We classify the 30 industries into terciles, and form $FVOL_A$ decile portfolios within each tercile. The $FVOL_A$ decile ranks are independent of the concavity terciles. The plot shows that the returns and alphas of the Low-High FVOL portfolios decrease from the top to bottom concavity terciles, both in the quarter after portfolio ranking (Q1) and during the 8 quarters using the JT8 approach.

Figure 7 further illustrates the effect of concavity on the FVOL-profitability relation using a similar sorted-portfolio approach. The plot shows that, based on operating profitability and return on equity, Low-High difference in profitability declines as we move from the top to the bottom concavity group. Based on gross profitability, the Low-High profitability difference is also higher for the top concavity group relative to the bottom group, although the pattern is not monotonic across terciles.

We further use Fama-MacBeth regressions to assess the significance of the concavity effect. The dependent variable is either monthly stock returns or quarterly profitability measures, during each of the 8 quarters after FVOL measurement. The explanatory variables include $FVOL_A$, Concavity, and their interaction terms. Concavity here is the quintile rank of the industry-level concavity measure. The cross-sectional regressions are performed monthly for stock returns and quarterly for profitability.

Panel A of Table 7 shows that in the stock return regression, the interaction term $FVOL \times Concavity$ is significantly negative for most of the quarters after FVOL measure-

ment and significantly negative in the JT8 regression. This confirms that higher concavity is associated with a more negative FVOL-return relation. Further, in Panels B to D, the interaction terms are also significantly negative for the profitability regressions, suggesting that higher concavity is associated with a more negative FVOL-profitability relation. Note that since the concavity measure is based on the data from the entire sample, we cannot say that higher concavity *predicts* a stronger FVOL effect.

Overall, the results above confirm that production function concavity, which economically represents decreasing marginal returns, plays an important role in explaining the FVOL effect on profitability and stock returns. This unique prediction distinguishes our model from alternative explanations of the FVOL effect, such as those based on financial market frictions or investor behavior.

5.3 The FVOL Effect in the Factor Zoo

Existing studies have identified a few hundred return-predictive stock characteristics, or asset pricing factors, many of which contain redundant information. Cochrane (2011) refers to this proliferation as the “factor zoo”. In this analysis, we ask how unique the FVOL-return relation is in light of the factor zoo. Feng, Giglio, and Xiu (2020) provide a “double-selection” approach to address this question in the presence of a high-dimensional set of factors. When assessing the incremental information of a newly proposed factor, they use LASSO regressions in the first step to select a sparse set of existing factors from a large pool of factor candidates, and then employ a second LASSO regression to correct potential inferential biases (i.e., omitted factors) caused by the sparsity imposed in the first step. We follow their approach.

Specifically, in Step 1, the average returns of test assets are regressed on the covariance between factors and returns using a cross-sectional LASSO regression:

$$\min_{\gamma, \lambda_h} \left\{ \sum_{i=1}^n (\bar{r}_i - \gamma - \sum_{h=1}^p C_{ih} \lambda_h)^2 + \tau_0 \sum_{h=1}^p |\lambda_h| \right\}, \quad (33)$$

where $\bar{r}_i$ is the average return of a test asset i , γ is the intercept, C_{ih} is the covariance between the i th test asset's returns and the h th existing factor, and τ_0 is a penalty parameter. This step identifies the existing factors that best explain the cross section of expected returns. Next, the covariance between the FVOL factor and returns is regressed on the covariance between all existing factors and returns, again using LASSO:

$$\min_{\xi, \mathbf{X}_h} \left\{ \sum_{i=1}^n (C_i^{FVOL} - \xi - \sum_{h=1}^p C_{ih} X_h)^2 + \tau_1 \sum_{h=1}^p |X_h| \right\}, \quad (34)$$

where C_i^{FVOL} is the covariance between the i th test asset's return and the FVOL factor, ξ is the intercept, and τ_1 is another penalty parameter. This step selects the existing factors whose exposures are highly correlated with the exposure of the FVOL factor in the cross section.

In Step 2, the average returns are regressed onto both the covariance between returns and the FVOL factor, as well as the covariance between returns and the subset of existing factors selected from Stage 1:

$$\min_{\delta, \lambda_0, \lambda_h} \left\{ \sum_{i=1}^n (\bar{r}_i - \delta - C_i^{FVOL} \lambda_0 - \sum_{h=1}^{p'} C'_{ih} \lambda'_h)^2 \right\}, \quad (35)$$

where C'_{ih} is the covariance between the i th test asset's return and the h th existing factor selected in Eqs. (33) and (34). The coefficient on the covariance between the FVOL factor and returns, λ_0 , represents the FVOL factor's SDF loading after accounting for the factor zoo.

We use the Low-High FVOL_A portfolio return to represent the new factor. It is evaluated against 135 existing factors from Feng et al. (2020), which are long-short portfolio returns based on firm characteristics. We include three different sets of test assets. They are 1) 750 portfolios based on 3×2 sorts on size and 125 stock characteristics, 2) 1825 portfolios based on 5×5 sorts on size and 73 stock characteristics, and 3) 202 portfolios based on an

assortment of sorts.¹⁰ In addition to LASSO as the factor selection method, we additionally use Elastic Net.¹¹

Table 8 presents the results based on the above combinations of test assets and factor selection methods. The reported SDF loadings of the Low-High FVOL return from Step 2 of the procedure are always significantly positive, showcasing the uniqueness of the FVOL-return relation within the broader factor zoo.

6 Conclusion

This paper empirically uncovers a significant negative relation between fundamental volatility and subsequent stock returns. This effect is pervasive: the negative impact on stock returns holds for FVOL measures constructed from a large number of accounting variables that represent resources or inputs used in firms' operations. The effect is also long-horizon, as the impact on stock returns persists for at least 8 quarters. The FVOL-return relation is unique when evaluated against a large set of asset pricing factors. In many respects, the FVOL effect is stronger than the idiosyncratic volatility effect.

We provide an explanation of the FVOL effect using a production-based asset pricing model. The model illustrates that when firms face diminishing marginal returns to inputs, high input volatility leads to lower expected profitability and lower expected returns. The model further suggests that the FVOL effect and the IVOL effect share a common origin. Consistent with model predictions, we find empirically that profitability stands out as the main channel for the FVOL-return relation. The FVOL-return relation and FVOL-profitability relation are stronger among firms facing more concave production functions. We also show that the long-short FVOL portfolio returns, as well as the long-short IVOL portfolio returns, vary over time in a similar fashion to the profitability factors, suggesting that

¹⁰They include 25 portfolios sorted by size and book-to-market ratio, 17 industry portfolios, 25 portfolios sorted by operating profitability and investment, 25 portfolios sorted by size and variance, 35 portfolios sorted by size and net issuance, 25 portfolios sorted by size and accruals, 25 portfolios sorted by size and momentum, and 25 portfolios sorted by size and beta.

¹¹We thank Feng, Giglio, and Xiu for making their data and programs available at the paper's website maintained by Journal of Finance, <https://onlinelibrary.wiley.com/doi/full/10.1111/jofi.12883>.

they share similar exposures to systematic risk. Together, these findings support a unified, rational asset pricing explanation for the long-standing puzzle of high-volatility/low-return.

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Figure 1. Alphas of FVOL Decile Portfolios

The left panel of this figure plots the four-factor alphas of decile portfolios formed on $FVOL_A$, the average rank of 14 fundamental volatility measures. The right panel plots the four-factor alphas of the JT8 portfolios. In this panel, the quarter- τ return of each FVOL decile is averaged across the $FVOL_A$ decile portfolios formed over the previous eight quarters, i.e., quarters quarter $\tau-1$ through $\tau-8$. All portfolios are value-weighted.

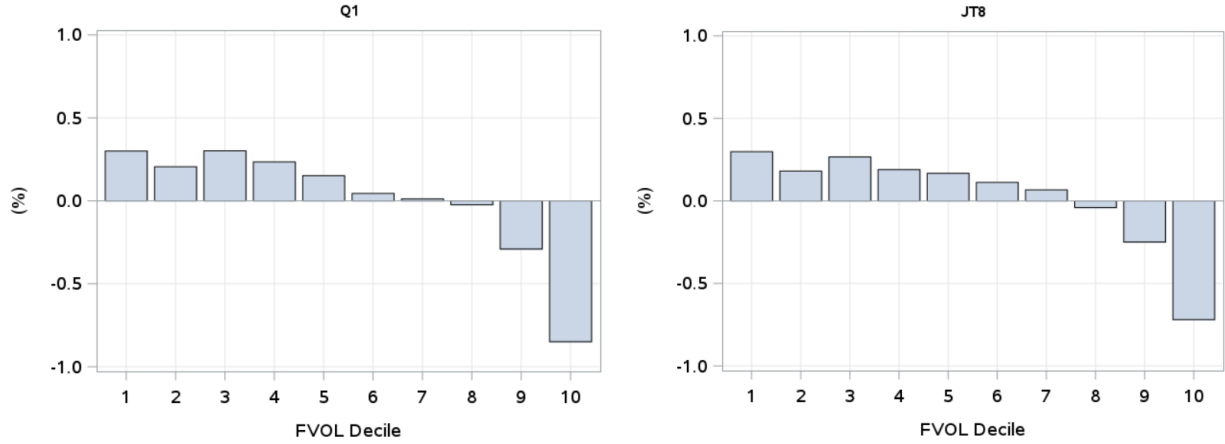


Figure 2. Market Cap Distribution Across FVOL Deciles

This figure plots the size shares of stocks in each of the 10 $FVOL_A$ deciles. $FVOL_A$ is defined as the average rank of 14 fundamental volatility measures. For each quarter, we compute the size share of a given $FVOL_A$ decile as the total market capitalization of the stocks in that decile divided by the total market capitalization across all $FVOL_A$ deciles. We then average these quarterly size shares over time.

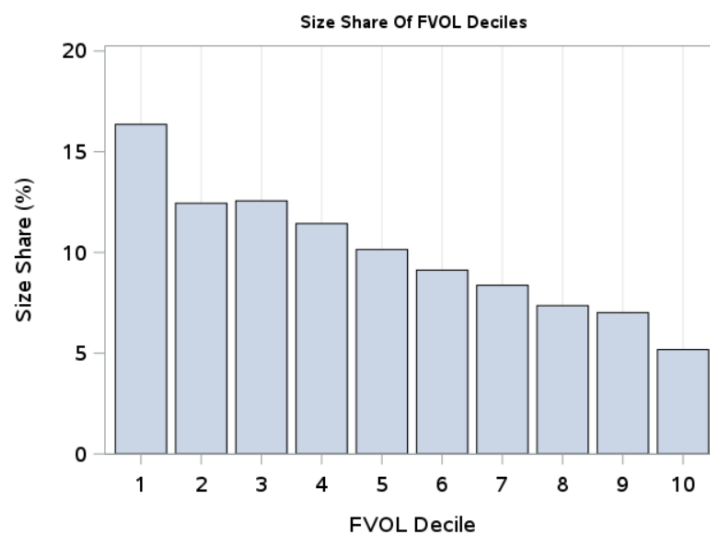
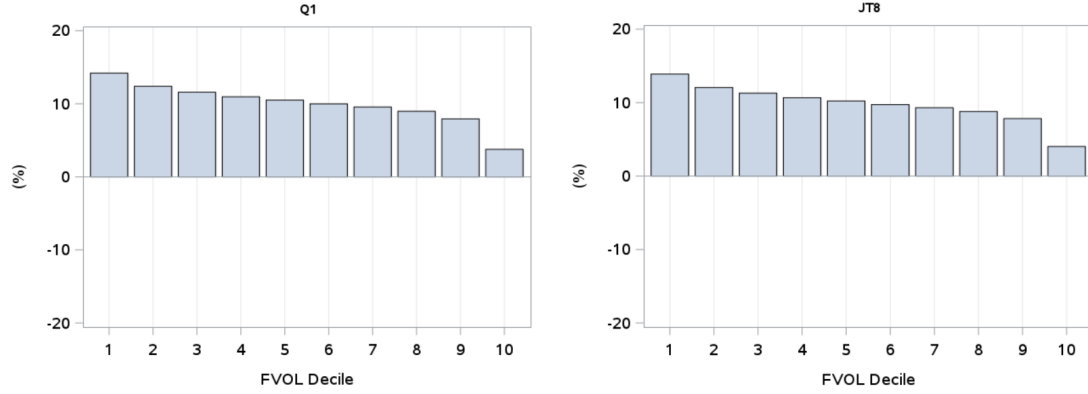


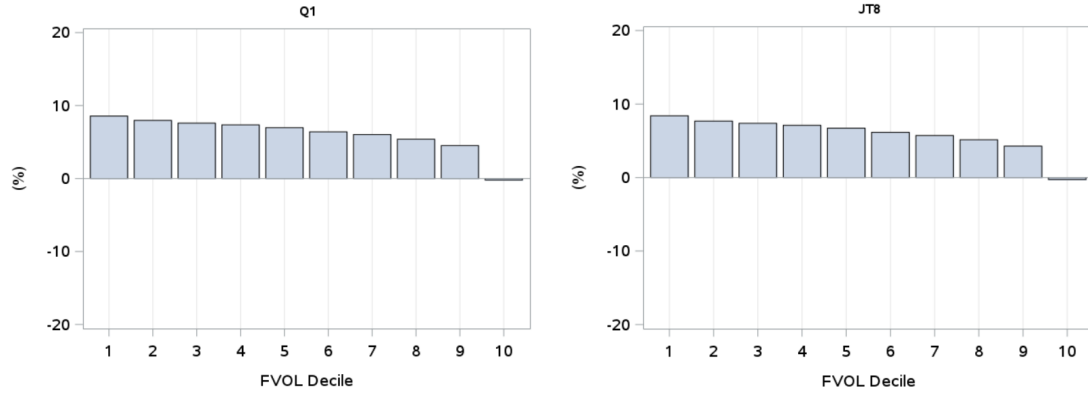
Figure 3. Profitability of FVOL Decile Portfolios

Panels A, B, and C report the average gross profitability, operating profitability, and return on equity for stocks in $FVOL_A$ deciles. $FVOL_A$ is the average rank of 14 fundamental volatility measures. In each panel, the left figure plots the average profitability in the quarter immediately after portfolio formation. The right figure plots profitability over the subsequent eight quarters using a non-overlapping portfolio approach, i.e., the “JT8” portfolios.

Panel A. Gross Profitability



Panel B. Operating Profitability



Panel C. Return On Equity

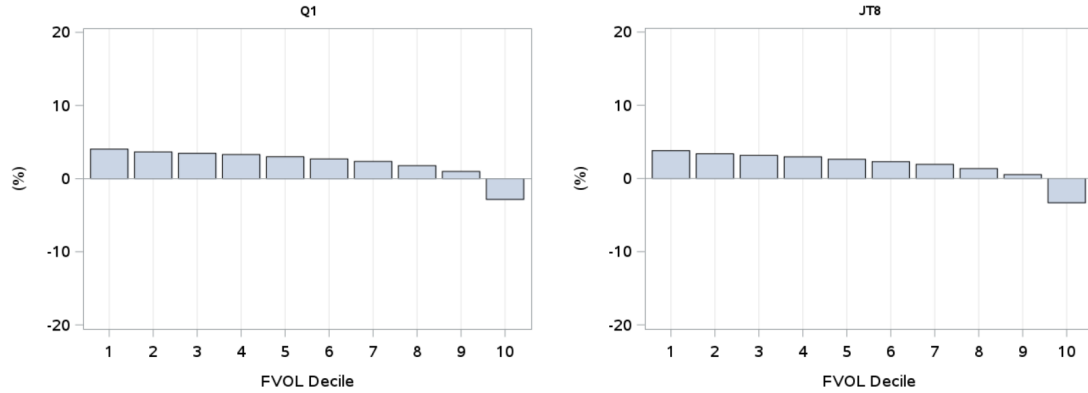


Figure 4. Unexplained FVOL-Return Relation

This figure plots the residual fraction of the FVOL effect that remains after controlling for lagged firm characteristics and contemporaneous profitability. The approach follows the four-stage decomposition of Hou and Loh (2016). In the first stage, we run monthly Fama–MacBeth regressions of excess returns on $FVOL_A$. In the second stage, we add candidate explanatory variables to these regressions. In the third stage, we regress $FVOL_A$ on the candidate variables. In the fourth stage, we decompose the FVOL–return relation into the fraction explained by the candidate variables and the residual unexplained fraction. In each figure, the dependent variable, future return, is measured during each of the subsequent 8 quarters (Q1 to Q8) after FVOL measurement. The candidate variables in the regression labeled “Lagged” include idiosyncratic volatility (IVOL), return skewness (Skew), coskewness (Coskew), lagged return (Lagret), frequency of zero daily returns (Zeroret), beta to average variance innovation ($AvgVar\beta$), Amihud illiquidity ratio (Illiq), marketcap (Size), book-to-market ratio (BM), lagged operating profitability (OP), asset growth (AG), standardized unexpected earnings (SUE), and accruals (ACC). Regressions labeled “Lagged+GP”, “Lagged+OP”, and “lagged+ROE” include all the explanatory variables used in the regression “Lagged” and additionally add the three contemporaneous profitability measures — gross profitability (GP), operating profitability (OP), and return on equity (ROE), respectively.

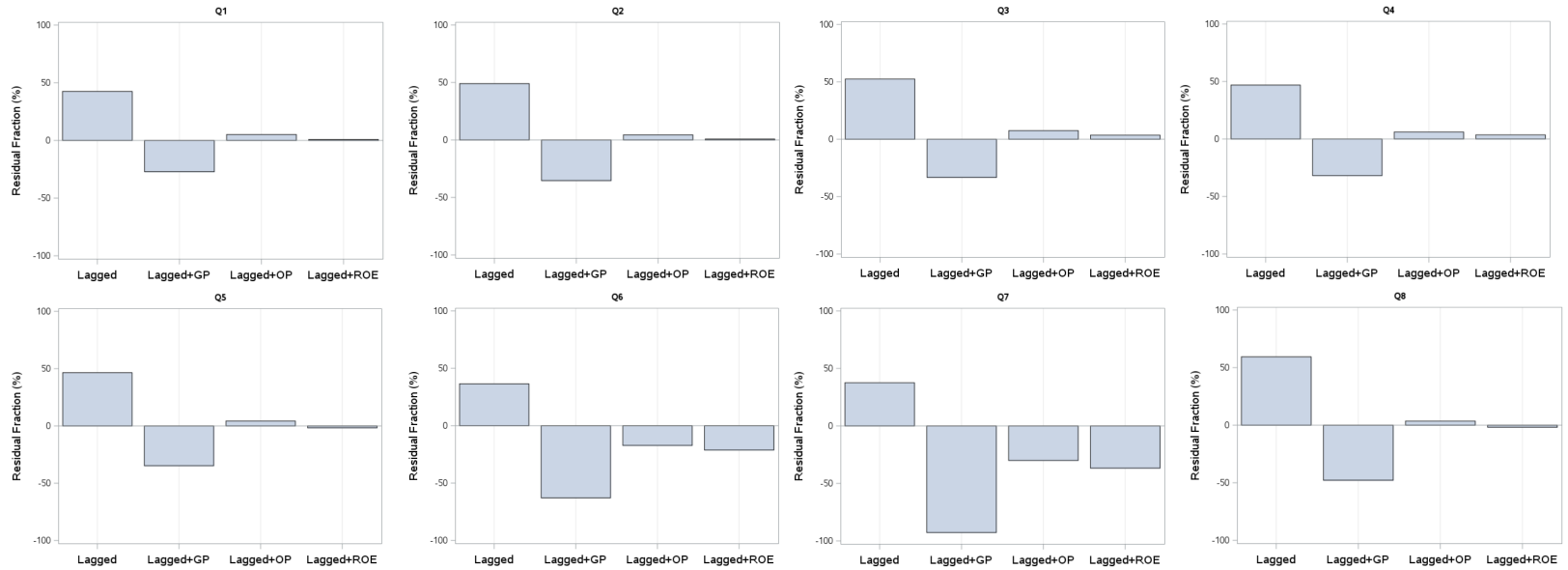
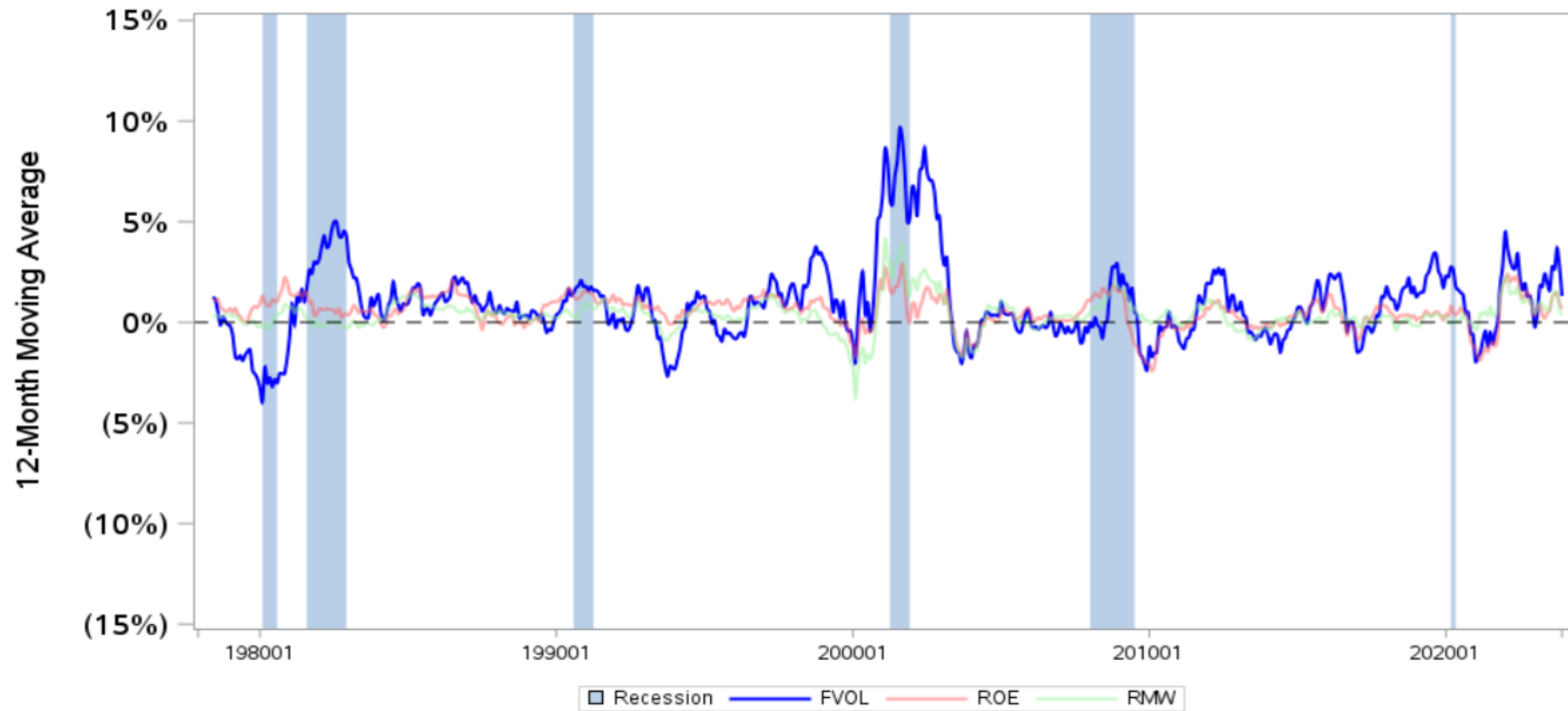


Figure 5. Time Series Plots of Low-High FVOL Portfolio Returns, Low-High IVOL Portfolio Returns, and Profitability Factors

Panel A of this figure plots the time series of returns on the Low-High FVOL_A portfolio, the Robust-Minus-Weak (RMW) factor in the five-factor model, and the return on equity (ROE) factor in the q-factor model. Panel B plots the time series of returns on the Low-High FVOL_A portfolio and on the Low-High IVOL portfolio. To highlight the slow-moving component, the returns plotted in both panels are moving averages over the past 12 months. The shaded areas in the plot indicate NBER recessions.



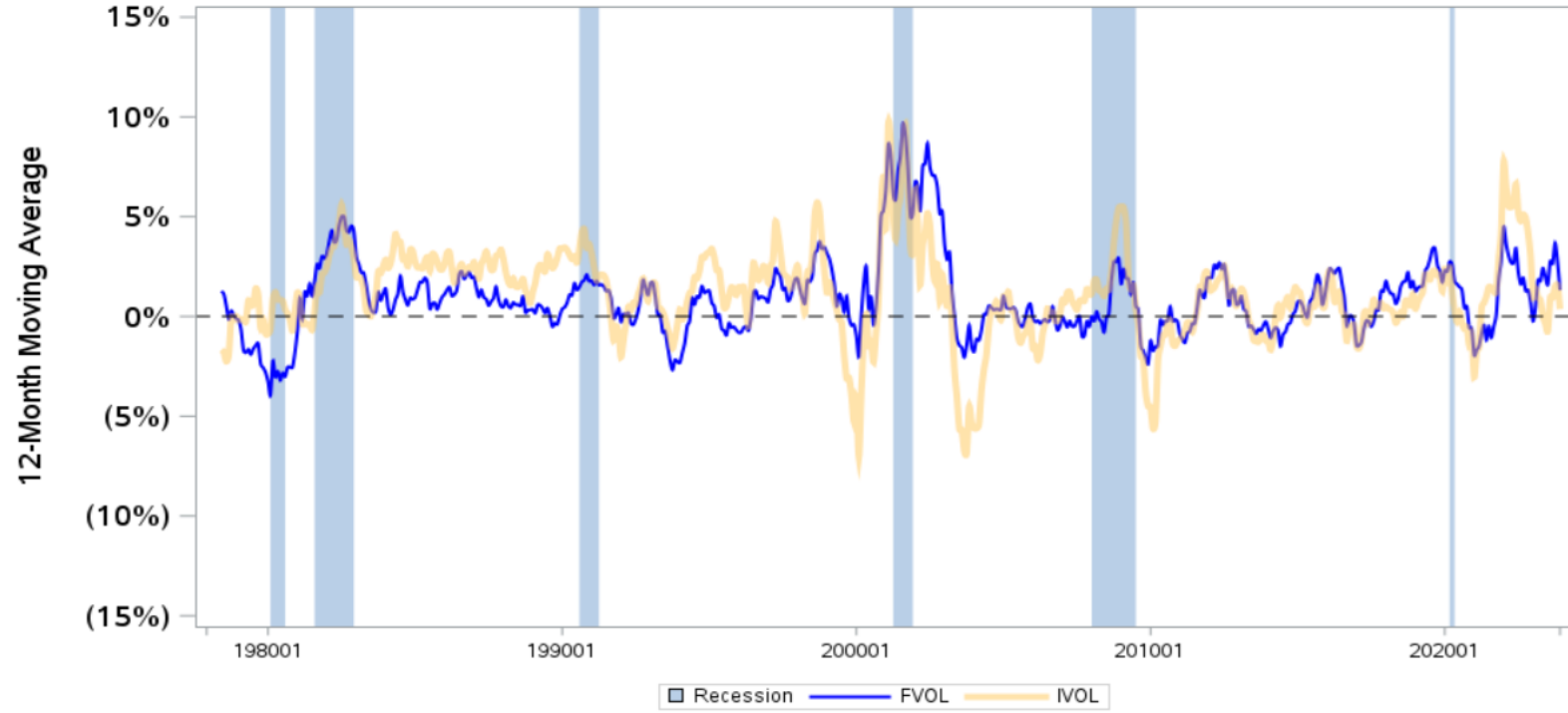


Figure 6. Production Function Concavity Across Industries

This figure plots the concavity measure of the production function for the 30 Fama–French industries. For each industry, we estimate the following regression over the full sample period: $\text{Ln}(\text{Sales}) = a + b\text{Ln}(\text{Assets}) + c\text{Ln}(\text{COGS}) + e$, using all available data during the sample period. Concavity is measured as $(c(1 - c) + b(1 - b))/2$. All accounting variables are winsorized at the 1st and 99th percentiles.

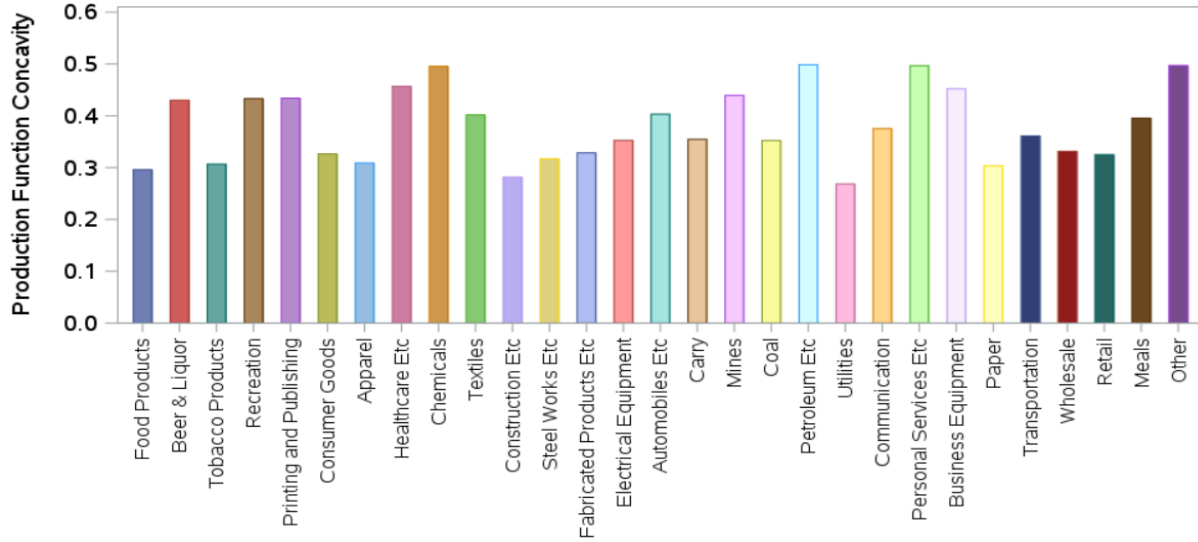


Figure 7. Effect of Production Function Concavity on the FVOL-Return Relation

This figure plots the returns and alphas of the Low–High FVOL portfolios within each concavity tercile (Top, Medium, and Bottom). Returns and alphas are measured in the quarter after FVOL measurement (Q1) as well as over the subsequent eight quarters using the JT8 approach (JT8). The concavity terciles are based on industry-level estimates of production-function concavity.

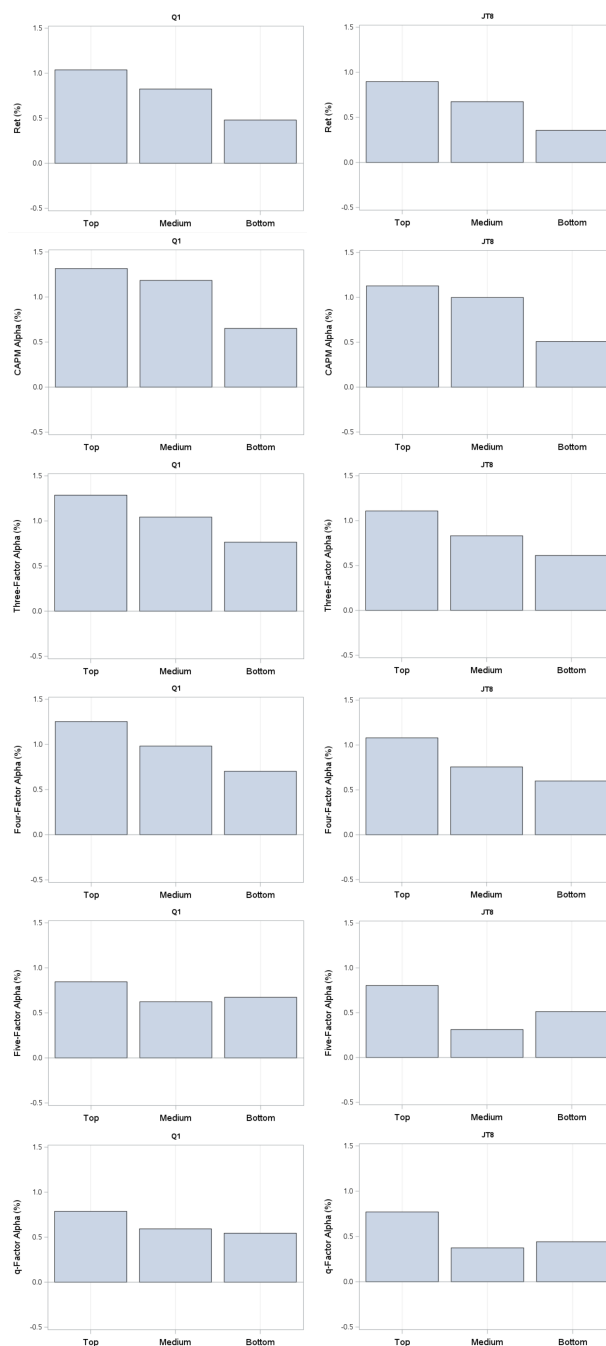


Figure 8. Effect of Production Function Concavity on the FVOL-Profitability Relation

This figure plots the three profitability measures of the Low–High FVOL portfolios within each concavity tercile (Top, Medium, and Bottom). Profitability is measured by gross profitability, operating profitability, and return on equity in the quarter after FVOL measurement (Q1), as well as over the subsequent eight quarters using the JT8 approach (JT8). The concavity terciles are based on industry-level estimates of production-function concavity.

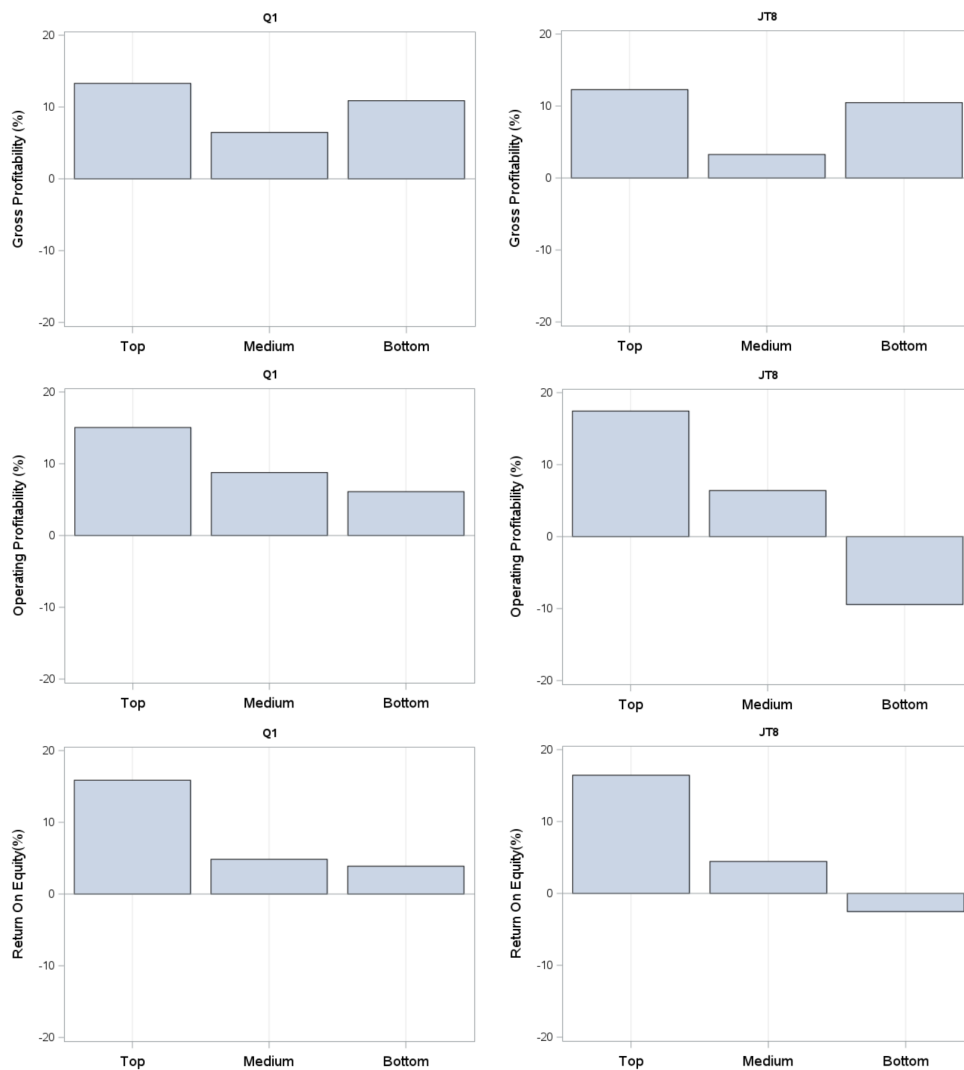


Table 1. Descriptive Statistics for FVOL

This table reports summary statistics for the fundamental volatility (FVOL) measures. Panel A presents the average cross-sectional distribution of the 14 individual $FVOL_k$ measures and their rank average across the 14 measures, $FVOL_A$. The cross-sectional statistics include the mean, standard deviation, average number of observations, and the 25th, 50th, and 75th percentiles. Panel B reports the average correlations among these FVOL measures. The first column of the table lists the Compustat variable names for the accounting variables used to construct the FVOL measures.

Panel A. Cross-sectional Distribution of FVOL Measures						
FVOL	Mean	Stdev	Nobs	25th Pctl	50th Pctl	75th Pctl
atq	16.99	621.38	1986	0.16	0.34	0.86
actq	14.90	535.34	1922	0.11	0.22	0.49
rectq	0.32	12.17	1932	0.05	0.09	0.17
invtq	0.14	2.53	1621	0.03	0.07	0.13
ppentq	1.16	37.98	1980	0.03	0.07	0.18
ltq	6.25	254.77	1985	0.12	0.25	0.60
lctq	3.24	122.55	1924	0.08	0.15	0.29
dlcq	2.08	82.13	1669	0.02	0.07	0.19
apq	1.03	37.01	1966	0.03	0.06	0.11
dlttq	5.23	213.44	1765	0.06	0.18	0.45
seqq	17.84	685.36	1986	0.07	0.18	0.50
xoprq	1.19	37.39	1956	0.06	0.11	0.22
cogsq	2.12	75.52	1960	0.05	0.09	0.18
xsgaq	1.85	66.09	1784	0.01	0.03	0.06
$FVOL_A$	49.48	20.19	1986	34.29	48.57	63.93

Table 1: Continued

Panel B. Rank Correlations among FVOL Measures															
	atq	actq	rectq	invtq	ppentq	ltq	lctq	dlcq	apq	dlttq	seqq	xoprq	cogsq	xsgaq	FVOL _A
atq	1.00														
actq	0.81	1.00													
rectq	0.60	0.63	1.00												
invtq	0.36	0.44	0.46	1.00											
ppentq	0.55	0.40	0.31	0.11	1.00										
ltq	0.83	0.63	0.53	0.31	0.54	1.00									
lctq	0.66	0.64	0.57	0.38	0.40	0.71	1.00								
dlcq	0.38	0.32	0.29	0.21	0.26	0.47	0.68	1.00							
apq	0.52	0.50	0.57	0.47	0.34	0.49	0.56	0.29	1.00						
dlttq	0.60	0.40	0.30	0.14	0.50	0.75	0.46	0.44	0.29	1.00					
seqq	0.72	0.69	0.49	0.26	0.43	0.57	0.51	0.28	0.40	0.42	1.00				
xoprq	0.45	0.45	0.53	0.43	0.28	0.40	0.45	0.18	0.48	0.22	0.36	1.00			
cogsq	0.37	0.36	0.48	0.40	0.27	0.36	0.40	0.18	0.47	0.20	0.28	0.90	1.00		
xsgaq	0.49	0.53	0.44	0.32	0.25	0.38	0.43	0.22	0.33	0.25	0.48	0.53	0.34	1.00	
FVOL _A	0.87	0.81	0.75	0.55	0.59	0.82	0.81	0.54	0.69	0.63	0.72	0.69	0.62	0.62	1.00

Table 2. Performance of Low-High FVOL Portfolios at Short Horizon

This table reports the performance of Low-High FVOL portfolios during the three months after portfolio formation. Performance is measured by average monthly returns (“Ret”), and by the monthly alphas based on CAPM, the three-factor, four-factor, five-factor, and q-factor models (labeled as “CAPM”, “FF3”, “FF4”, “FF5”, and “q4” respectively). Each quarter, stocks are sorted into deciles based on each of the 14 FVOL measures and on $FVOL_A$. The Low-High portfolio takes long (short) positions in stocks in the bottom (top) FVOL decile. Portfolios are value-weighted. Returns and alphas are expressed in percentage points (%). t -statistics are reported in parentheses.

FVOL	Ret	CAPM	FF3	FF4	FF5	q4
atq	0.66 (3.26)	0.96 (5.20)	0.90 (5.25)	0.86 (4.93)	0.38 (2.49)	0.34 (2.01)
actq	0.46 (1.72)	0.84 (3.39)	0.65 (3.34)	0.62 (3.13)	-0.06 (-0.38)	-0.07 (-0.32)
rectq	0.58 (2.58)	0.87 (4.12)	0.83 (4.28)	0.81 (4.09)	0.36 (1.99)	0.33 (1.67)
invtq	0.64 (3.48)	0.75 (4.14)	0.85 (4.96)	0.81 (4.62)	0.78 (4.50)	0.73 (4.13)
ppentq	0.58 (3.35)	0.65 (3.76)	0.75 (4.40)	0.78 (4.51)	0.65 (3.91)	0.60 (3.46)
ltq	0.55 (3.11)	0.75 (4.47)	0.78 (4.74)	0.74 (4.43)	0.50 (3.13)	0.45 (2.69)
lctq	0.71 (4.19)	0.90 (5.50)	0.87 (5.53)	0.86 (5.34)	0.58 (3.85)	0.57 (3.53)
dlcq	0.30 (1.90)	0.22 (1.42)	0.36 (2.36)	0.47 (3.11)	0.46 (3.02)	0.50 (3.16)
apq	0.39 (2.20)	0.58 (3.42)	0.62 (3.93)	0.60 (3.78)	0.40 (2.59)	0.33 (2.08)
dlttq	0.47 (2.89)	0.50 (3.11)	0.59 (3.68)	0.65 (3.99)	0.62 (3.74)	0.62 (3.67)
seqq	0.67 (2.94)	0.96 (4.58)	0.81 (4.26)	0.76 (3.93)	0.24 (1.45)	0.20 (1.05)
xoprq	0.77 (3.69)	1.06 (5.41)	1.06 (6.36)	1.02 (5.99)	0.57 (3.81)	0.54 (3.27)
cogsq	0.62 (3.18)	0.88 (4.80)	0.92 (5.76)	0.85 (5.24)	0.54 (3.62)	0.53 (3.31)
xsgaq	0.40 (2.29)	0.60 (3.61)	0.43 (2.87)	0.33 (2.17)	0.02 (0.18)	0.00 (-0.03)
$FVOL_A$	0.93 (4.09)	1.25 (5.89)	1.21 (6.21)	1.15 (5.85)	0.73 (4.10)	0.67 (3.45)

Table 3. Performance of Low-High FVOL Portfolios over Long Horizon

This table reports the performance of Low-High FVOL_A portfolios during each of the eight quarters (Q1 through Q8) after portfolio formation. The row labeled “JT8” summarizes the performance over these eight quarters using the non-overlapping portfolio approach of Jegadeesh and Titman (1993). Performance is measured by average monthly returns (“Ret”), and by the monthly alphas based on CAPM, the three-factor, four-factor, five-factor, and q-factor models (labeled as “CAPM”, “FF3”, “FF4”, “FF5”, and “q4” respectively). Each quarter, stocks are sorted into deciles based on FVOL_A. The Low-High portfolio takes long (short) positions in stocks in the bottom (top) FVOL_A decile. Portfolios are value-weighted. Returns and alphas are expressed in percentage points (%). *t*-statistics are reported in parentheses.

Quarter	Ret	CAPM	FF3	FF4	FF5	q4
Q1	0.93 (4.09)	1.25 (5.89)	1.21 (6.21)	1.15 (5.85)	0.73 (4.10)	0.67 (3.45)
Q2	0.96 (4.29)	1.30 (6.26)	1.25 (6.53)	1.15 (5.96)	0.79 (4.48)	0.71 (3.74)
Q3	0.88 (4.04)	1.23 (6.18)	1.18 (6.38)	1.07 (5.73)	0.74 (4.31)	0.68 (3.69)
Q4	0.83 (3.96)	1.16 (6.02)	1.11 (6.18)	1.00 (5.57)	0.72 (4.24)	0.65 (3.63)
Q5	0.77 (3.68)	1.08 (5.61)	1.03 (5.73)	0.94 (5.22)	0.67 (3.90)	0.63 (3.44)
Q6	0.65 (3.19)	0.93 (4.86)	0.87 (4.91)	0.82 (4.58)	0.55 (3.26)	0.51 (2.79)
Q7	0.75 (3.60)	1.01 (5.11)	0.97 (5.30)	0.96 (5.16)	0.63 (3.63)	0.60 (3.18)
Q8	0.70 (3.45)	0.96 (4.98)	0.93 (5.13)	0.92 (4.98)	0.64 (3.62)	0.65 (3.48)
JT8	0.81 (4.04)	1.11 (6.03)	1.08 (6.41)	1.02 (5.96)	0.70 (4.42)	0.65 (3.82)

Table 4. Performance of Portfolios Sorted On FVOL and IVOL

Panels A and C report average returns and alphas for Low–High quintile portfolios formed on FVOL_A and IVOL, respectively. Panel B reports average returns and alphas for Low–High FVOL_A quintile portfolios that control for IVOL using a double-sorting procedure. Each quarter, we independently sort stocks by FVOL_A and IVOL into 5×5 groups and form value-weighted portfolios within each group. We then average the returns of the five portfolios that share the same FVOL_A quintile rank but have different IVOL ranks and compute the return difference between the bottom and top FVOL_A groups (Low–High). In Panel D, we follow the same double-sorting procedure as in Panel B but average the returns of portfolios with the same IVOL rank and different FVOL_A ranks. We report performance during the first quarter after portfolio formation (Q1) and the non-overlapping performance over the subsequent eight holding quarters (JT8), following Jegadeesh and Titman (1993). Alphas are from the CAPM, three-factor, four-factor, five-factor, and q-factor models (labeled as “CAPM”, “FF3”, “FF4”, “FF5”, and “q4” respectively). Returns and alphas are expressed in percentage points (%), and *t*-statistics are reported in parentheses.

Panel A. Unconditional Low-High FVOL Quintile Portfolio						
	Ret	CAPM	FF3	FF4	FF5	q4
Q1	0.72 (3.61)	1.00 (5.44)	0.91 (5.34)	0.82 (4.82)	0.55 (3.55)	0.45 (2.73)
JT8	0.50 (2.92)	0.72 (4.47)	0.62 (4.29)	0.61 (4.17)	0.44 (3.19)	0.40 (2.73)
Panel B. Low-High FVOL Portfolio Controlling for IVOL						
	Ret	CAPM	FF3	FF4	FF5	q4
Q1	0.64 (3.54)	0.87 (5.03)	0.77 (4.69)	0.74 (4.46)	0.44 (2.92)	0.38 (2.32)
JT8	0.66 (4.37)	0.85 (5.83)	0.77 (5.58)	0.73 (5.26)	0.54 (4.20)	0.50 (3.57)
Panel C. Unconditional Low-High IVOL Quintile Portfolio						
	Ret	CAPM	FF3	FF4	FF5	q4
Q1	0.58 (1.83)	1.06 (3.67)	0.81 (3.69)	0.60 (2.79)	0.17 (0.90)	0.00 (-0.02)
JT8	0.11 (0.41)	0.61 (2.72)	0.42 (2.65)	0.33 (2.05)	-0.04 (-0.29)	-0.15 (-0.96)
Panel D. Low-High IVOL Portfolio Controlling for FVOL						
	Ret	CAPM	FF3	FF4	FF5	q4
Q1	0.39 (1.40)	0.82 (3.19)	0.60 (3.18)	0.41 (2.23)	0.09 (0.50)	-0.07 (-0.36)
JT8	-0.01 (-0.06)	0.44 (2.15)	0.27 (1.97)	0.18 (1.28)	-0.13 (-1.03)	-0.21 (-1.55)

Table 5. FVOL-Profitability Relation: Multivariate Regressions

This table reports the relation between FVOL and profitability using quarterly Fama–MacBeth regressions. The dependent variable is one of three profitability measures—gross profitability (Panel A), operating profitability (Panel B), or return on equity (Panel C)—measured in each of the subsequent eight quarters (Q1 through Q8). The main explanatory variable is FVOL_A. The control variables include past profitability (PP), idiosyncratic volatility (IVOL), book-to-market ratio (BM), market capitalization (SIZE), a dummy for negative profitability (NP), the negative and positive components of accruals (-ACCBE and +ACCBE), asset growth (AG), no-dividend dummy (NODIV), dividends-to-book ratio (DIVBE), returns in year y-1 (RET_1yr), and returns in year y-3 to y-2 (RET_23yr), Ohlson’s probability of default (O_Score), and Piotroski’s composite index of firm strength (F_Score). The columns labeled with odd numbers (1, 3, ..., 15) report univariate regressions in which the only explanatory variable is FVOL_A. The columns labeled with even numbers (2, 4, ..., 16) report multivariate regressions that also include the control variables. The *t*-statistics reported in parentheses are based on Newey–West standard errors with a 12-quarter lag.

Panel A. Dependent Variable: Gross Profitability																
Explanatory	Q1		Q2		Q3		Q4		Q5		Q6		Q7		Q8	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	16.47 (91.69)	10.91 (39.31)	16.20 (92.36)	10.88 (40.59)	16.05 (88.50)	10.78 (40.78)	15.90 (85.15)	10.36 (43.97)	15.77 (82.26)	10.72 (42.28)	15.61 (83.72)	10.76 (42.88)	15.48 (82.16)	10.67 (44.42)	15.37 (80.67)	10.29 (46.39)
FVOL	-0.14 (-39.16)	-0.02 (-29.77)	-0.14 (-41.65)	-0.02 (-24.23)	-0.14 (-43.57)	-0.02 (-18.38)	-0.13 (-42.07)	-0.02 (-10.43)	-0.13 (-43.16)	-0.02 (-13.78)	-0.13 (-43.50)	-0.03 (-14.54)	-0.13 (-44.45)	-0.02 (-13.99)	-0.13 (-43.54)	-0.02 (-8.83)
PP		6.04 (74.33)		5.71 (82.27)		5.63 (84.68)		5.99 (67.92)		5.39 (80.05)		5.16 (83.54)		5.18 (73.52)		5.56 (63.03)
IVOL		-0.01 (-1.25)		-0.05 (-2.98)		-0.06 (-3.04)		-0.06 (-2.97)		-0.03 (-1.17)		-0.01 (-0.34)		0.02 (0.52)		0.00 (0.06)
BM		-0.28 (-19.78)		-0.32 (-14.63)		-0.28 (-13.46)		-0.11 (-3.84)		-0.26 (-8.69)		-0.29 (-7.76)		-0.23 (-5.77)		-0.09 (-2.20)
SIZE		-0.21 (-18.03)		-0.24 (-16.68)		-0.23 (-12.94)		-0.14 (-8.89)		-0.23 (-11.08)		-0.25 (-9.75)		-0.22 (-8.54)		-0.15 (-5.92)
NP		0.43 (5.95)		0.40 (5.39)		0.33 (5.42)		0.42 (7.84)		0.43 (5.70)		0.40 (5.21)		0.39 (5.30)		0.47 (7.18)
-ACCBE		-0.01 (-1.18)		-0.02 (-1.41)		-0.03 (-2.26)		-0.04 (-2.44)		-0.03 (-1.99)		-0.04 (-2.46)		-0.03 (-2.00)		-0.04 (-2.04)
+ACCBE		-0.01 (-1.61)		-0.02 (-1.72)		-0.02 (-1.49)		-0.03 (-1.74)		-0.02 (-1.01)		-0.02 (-1.14)		0.00 (-0.18)		-0.01 (-0.87)
AG		-0.01 (-1.33)		-0.02 (-1.58)		-0.04 (-2.29)		-0.05 (-2.80)		-0.06 (-3.24)		-0.05 (-2.29)		-0.05 (-2.18)		-0.03 (-1.55)
NODIV		0.04 (3.76)		0.05 (2.93)		0.07 (4.06)		0.06 (3.08)		0.06 (3.22)		0.06 (2.73)		0.07 (2.78)		0.06 (2.75)
DIVBE		-0.02 (-1.21)		-0.01 (-0.72)		0.01 (0.47)		0.02 (0.94)		0.01 (0.48)		0.01 (0.30)		0.03 (1.13)		0.04 (1.54)
RET_1yr		0.18 (13.53)		0.17 (10.17)		0.06 (3.78)		-0.10 (-4.88)		-0.09 (-3.57)		-0.12 (-3.67)		-0.21 (-5.66)		-0.32 (-8.06)
RET_23yr		-0.07 (-5.73)		-0.13 (-7.81)		-0.18 (-8.28)		-0.21 (-9.26)		-0.25 (-9.18)		-0.29 (-8.60)		-0.30 (-8.83)		-0.33 (-9.23)
Oscore		-0.20 (-10.56)		-0.26 (-9.95)		-0.25 (-9.01)		-0.19 (-6.35)		-0.29 (-9.20)		-0.31 (-9.37)		-0.28 (-9.09)		-0.20 (-5.91)
Fscore		-0.05 (-6.26)		-0.05 (-4.86)		-0.05 (-4.03)		-0.04 (-2.90)		-0.07 (-3.51)		-0.08 (-4.07)		-0.09 (-4.15)		-0.07 (-3.13)
Adjusted R^2 (%)	15.73	80.74	15.07	73.27	14.90	71.74	14.50	75.40	14.22	66.44	13.88	62.70	13.54	62.27	13.20	66.44

Panel B. Dependent Variable: Operating Profitability																
Explanatory	Q1		Q2		Q3		Q4		Q5		Q6		Q7		Q8	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	11.52	7.64	11.22	7.70	11.03	7.43	10.87	6.66	10.77	7.41	10.65	7.61	10.53	7.38	10.43	6.74
	(23.69)	(49.77)	(23.66)	(59.71)	(24.60)	(56.71)	(23.74)	(55.78)	(23.63)	(57.84)	(22.93)	(54.40)	(23.15)	(51.76)	(22.21)	(42.72)
FVOL	-0.12	-0.04	-0.12	-0.04	-0.12	-0.04	-0.11	-0.03	-0.11	-0.04	-0.11	-0.05	-0.11	-0.04	-0.11	-0.03
	(-9.13)	(-32.51)	(-9.96)	(-34.69)	(-10.31)	(-27.46)	(-10.21)	(-10.39)	(-10.12)	(-19.57)	(-10.16)	(-20.52)	(-10.30)	(-17.69)	(-10.13)	(-10.04)
PP		4.24		3.42		3.46		4.64		2.88		2.39		2.61		3.74
		(11.02)		(9.87)		(11.27)		(23.41)		(9.91)		(8.61)		(10.23)		(20.40)
IVOL		-0.43		-0.49		-0.46		-0.37		-0.48		-0.50		-0.44		-0.37
		(-9.85)		(-9.51)		(-8.18)		(-7.43)		(-7.77)		(-8.09)		(-6.44)		(-6.32)
BM		-0.46		-0.51		-0.41		-0.16		-0.41		-0.43		-0.33		-0.13
		(-5.04)		(-5.02)		(-4.16)		(-2.72)		(-4.07)		(-3.85)		(-3.13)		(-1.61)
SIZE		0.17		0.23		0.26		0.27		0.36		0.41		0.45		0.42
		(5.08)		(5.69)		(5.54)		(6.15)		(6.79)		(6.55)		(6.91)		(7.34)
NP		-0.08		-0.14		-0.17		-0.09		-0.20		-0.19		-0.16		-0.09
		(-2.31)		(-3.27)		(-3.93)		(-1.68)		(-3.96)		(-3.59)		(-2.79)		(-1.81)
-ACCBE		-0.38		-0.42		-0.36		-0.22		-0.35		-0.41		-0.33		-0.25
		(-8.47)		(-9.75)		(-8.55)		(-4.69)		(-8.42)		(-8.69)		(-6.49)		(-4.49)
+ACCBE		-0.10		-0.16		-0.18		-0.16		-0.21		-0.21		-0.18		-0.16
		(-4.42)		(-6.77)		(-7.41)		(-6.53)		(-6.58)		(-5.91)		(-4.18)		(-3.45)
AG		0.11		0.10		0.07		-0.02		0.02		0.03		0.01		-0.03
		(5.23)		(3.15)		(2.03)		(-0.65)		(0.47)		(0.69)		(0.39)		(-0.68)
NODIV		0.06		0.05		0.06		0.01		0.02		0.02		0.02		-0.01
		(3.66)		(2.21)		(2.06)		(0.25)		(0.67)		(0.40)		(0.55)		(-0.13)
DIVBE		0.39		0.47		0.46		0.35		0.50		0.54		0.53		0.40
		(6.76)		(7.19)		(8.85)		(6.84)		(8.45)		(7.97)		(8.40)		(6.37)
RET_1yr		0.76		0.80		0.65		0.28		0.50		0.49		0.31		0.01
		(10.69)		(11.02)		(10.08)		(8.81)		(7.33)		(5.91)		(3.59)		(0.18)
RET_23yr		0.16		0.13		0.06		-0.09		-0.02		-0.06		-0.11		-0.26
		(4.24)		(3.04)		(1.32)		(-2.24)		(-0.31)		(-1.12)		(-2.21)		(-5.22)
Oscore		-0.07		-0.12		-0.14		-0.14		-0.16		-0.17		-0.16		-0.15
		(-1.52)		(-2.26)		(-2.57)		(-3.78)		(-2.82)		(-2.95)		(-2.48)		(-2.46)
Fscore		0.15		0.19		0.18		0.14		0.19		0.20		0.18		0.15
		(4.87)		(4.88)		(5.62)		(5.11)		(4.29)		(4.27)		(4.03)		(4.19)
Adjusted R^2 (%)	9.32	49.70	8.51	37.44	8.39	36.21	8.09	44.55	7.90	29.68	7.51	25.28	7.19	24.90	6.96	31.67

Panel C. Dependent Variable: Return On Equity																
Explanatory	Q1		Q2		Q3		Q4		Q5		Q6		Q7		Q8	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Intercept	6.54	3.32	6.34	3.40	6.26	3.30	6.18	2.95	6.12	3.22	6.02	3.32	5.94	3.21	5.90	2.93
	(14.96)	(36.22)	(16.03)	(34.97)	(16.42)	(31.10)	(16.52)	(26.83)	(16.48)	(27.59)	(16.20)	(28.71)	(16.45)	(25.93)	(16.33)	(22.59)
FVOL	-0.10	-0.03	-0.09	-0.03	-0.09	-0.03	-0.10	-0.03	-0.10	-0.03	-0.09	-0.04	-0.09	-0.04	-0.09	-0.03
	(-7.86)	(-11.01)	(-8.35)	(-13.13)	(-8.60)	(-12.66)	(-8.84)	(-9.90)	(-8.95)	(-11.92)	(-8.88)	(-12.37)	(-9.01)	(-12.17)	(-9.20)	(-9.90)
PP		2.69		2.07		2.05		2.54		1.69		1.40		1.47		2.02
		(9.31)		(8.95)		(9.40)		(15.15)		(8.79)		(7.40)		(7.87)		(13.81)
IVOL		-0.60		-0.60		-0.59		-0.53		-0.64		-0.63		-0.58		-0.55
		(-7.71)		(-9.28)		(-9.02)		(-7.70)		(-8.73)		(-8.75)		(-7.72)		(-7.52)
BM		-0.23		-0.29		-0.24		-0.12		-0.22		-0.25		-0.18		-0.06
		(-3.54)		(-4.07)		(-3.41)		(-2.32)		(-3.28)		(-3.37)		(-2.69)		(-1.23)
SIZE		0.02		0.04		0.06		0.10		0.11		0.15		0.18		0.19
		(0.54)		(1.02)		(1.30)		(2.47)		(2.23)		(2.80)		(3.09)		(3.42)
NP		-0.18		-0.16		-0.23		-0.25		-0.23		-0.14		-0.20		-0.22
		(-6.48)		(-4.67)		(-6.37)		(-5.09)		(-6.11)		(-4.47)		(-4.74)		(-5.19)
-ACCBE		0.03		0.03		0.01		0.04		0.07		0.08		0.06		0.05
		(1.07)		(1.01)		(0.20)		(0.89)		(2.12)		(1.68)		(1.29)		(1.10)
+ACCBE		-0.10		-0.11		-0.13		-0.11		-0.15		-0.14		-0.10		-0.11
		(-3.92)		(-3.73)		(-4.32)		(-5.34)		(-5.06)		(-3.77)		(-2.20)		(-2.38)
AG		0.00		-0.05		-0.08		-0.12		-0.13		-0.16		-0.18		-0.16
		(0.08)		(-2.29)		(-2.69)		(-5.34)		(-4.67)		(-4.81)		(-5.86)		(-5.33)
NODIV		0.03		0.00		-0.01		-0.05		-0.06		-0.07		-0.07		-0.07
		(2.03)		(0.13)		(-0.48)		(-1.88)		(-1.87)		(-2.19)		(-2.07)		(-2.07)
DIVBE		0.36		0.40		0.38		0.33		0.40		0.42		0.41		0.37
		(5.99)		(6.08)		(7.17)		(7.13)		(7.70)		(8.01)		(8.54)		(8.08)
RET_1yr		0.77		0.88		0.77		0.56		0.68		0.64		0.48		0.28
		(19.22)		(22.14)		(19.56)		(11.05)		(15.17)		(12.81)		(8.60)		(4.77)
RET_23yr		0.28		0.26		0.18		0.08		0.11		0.10		0.05		-0.07
		(9.77)		(9.08)		(6.54)		(2.78)		(3.46)		(2.95)		(1.22)		(-1.86)
Oscore		-0.46		-0.52		-0.51		-0.47		-0.57		-0.60		-0.59		-0.53
		(-8.58)		(-8.87)		(-8.59)		(-8.95)		(-9.46)		(-9.58)		(-8.79)		(-8.02)
Fscore		0.09		0.12		0.11		0.11		0.13		0.14		0.12		0.10
		(4.08)		(4.15)		(4.15)		(3.83)		(3.76)		(3.50)		(3.64)		(2.99)
Adjusted R^2 (%)	8.23	38.31	7.74	30.56	7.61	28.62	7.37	32.65	7.14	23.03	6.80	20.02	6.56	19.23	6.35	22.13

Table 6. Decomposing the FVOL-Return Relation via Multivariate Regressions

This table reports results from Fama–MacBeth regressions of monthly stock returns on FVOL, low-risk variables, and future profitability. The candidate variables in the regression labeled “Lagged” include idiosyncratic volatility (IVOL), return skewness (Skew), coskewness (Coskew), lagged return (Lagret), Amihud illiquidity ratio (Illiq), frequency of zero daily returns (Zeroret), marketcap (Size), book-to-market ratio (BM), asset growth (Ag), lagged operating profitability (Op), accruals (Acc), standardized unexpected earnings (SUE), and beta to average variance innovation ($\text{AvgVar}\beta$). In Panel B, the analysis is extended to 8 quarters. Regression (3), (4) and (5) control for contemporaneous gross profitability (GP), operating profitability (OP), and return on equity (ROE). The contemporaneous profitability variables are measured during the same quarter as the dependent variable. In rows “Q1” to “Q8”, the dependent variable (future return) and contemporaneous profitability are measured from the first through the eighth quarter after FVOL measurement. The reported coefficients are multiplied by 100. The t -statistics are reported in parentheses.

Panel A. Returns During Q1											
		Regression									
Quarter	Variable	(1)		(2)		(3)		(4)		(5)	
		coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Q1	Intercept	1.694	(9.05)	1.445	(7.14)	0.889	(4.52)	1.161	(5.77)	1.127	(5.58)
	FVOL	-0.012	(-4.15)	-0.007	(-3.66)	0.004	(2.16)	-0.001	(-0.69)	-0.001	(-0.32)
	IVOL			-0.128	(-2.30)	-0.145	(-2.63)	-0.097	(-1.77)	-0.075	(-1.37)
	Skew			0.062	(2.34)	0.066	(2.52)	0.062	(2.39)	0.057	(2.19)
	Coskew			-0.020	(-0.81)	-0.017	(-0.69)	-0.017	(-0.71)	-0.016	(-0.67)
	Lagret			-0.123	(-2.55)	-0.151	(-3.15)	-0.192	(-4.00)	-0.212	(-4.39)
	Illiq			-0.055	(-1.78)	-0.061	(-1.97)	-0.075	(-2.42)	-0.079	(-2.59)
	Maxret			-0.068	(-1.10)	-0.075	(-1.23)	-0.043	(-0.71)	-0.020	(-0.33)
	Zeroret			-0.092	(-3.70)	-0.080	(-3.24)	-0.073	(-2.94)	-0.056	(-2.29)
	Size			-0.145	(-3.08)	-0.030	(-0.63)	-0.171	(-3.68)	-0.155	(-3.34)
	BM			0.117	(2.76)	0.295	(6.96)	0.221	(5.06)	0.229	(5.29)
	Ag			-0.147	(-5.46)	-0.142	(-5.28)	-0.097	(-3.60)	-0.096	(-3.62)
	Op			0.104	(3.78)	0.035	(1.26)	-0.222	(-8.50)	-0.162	(-6.12)
	Acc			-0.047	(-2.09)	-0.044	(-1.99)	0.018	(0.82)	-0.060	(-2.70)
	SUE			0.192	(7.53)	0.135	(5.34)	0.066	(2.69)	0.034	(1.42)
	$\text{AvgVar}\beta$			0.013	(0.57)	0.019	(0.79)	0.012	(0.49)	0.011	(0.47)
	Contemp. Profitability					0.608	(17.30)	0.899	(24.87)	0.996	(26.10)
Panel B. Returns During Q2 to Q8											
Q2	FVOL	-0.010	(-3.27)	-0.007	(-3.33)	0.005	(2.39)	-0.001	(-0.48)	0.000	(-0.24)
Q3	FVOL	-0.009	(-3.06)	-0.007	(-3.37)	0.004	(2.12)	-0.001	(-0.63)	-0.001	(-0.40)
Q4	FVOL	-0.011	(-3.45)	-0.006	(-3.22)	0.005	(2.32)	-0.001	(-0.49)	-0.001	(-0.32)
Q5	FVOL	-0.009	(-2.97)	-0.005	(-2.69)	0.004	(2.22)	-0.001	(-0.28)	0.000	(0.06)
Q6	FVOL	-0.007	(-2.47)	-0.003	(-1.79)	0.006	(3.31)	0.001	(0.79)	0.002	(0.99)
Q7	FVOL	-0.005	(-1.86)	-0.003	(-1.31)	0.007	(3.50)	0.002	(1.04)	0.002	(1.28)
Q8	FVOL	-0.007	(-2.37)	-0.005	(-2.64)	0.004	(2.37)	0.000	(-0.16)	0.000	(0.07)

Table 7. The Effect of Production Function Concavity

This table reports the effect of production-function concavity on the FVOL–return and FVOL–profitability relations, based on Fama–MacBeth regressions. The dependent variable is either the monthly stock return (Panel A) or one of three profitability measures—gross profitability, operating profitability, and return on equity (Panels B–D, respectively). All dependent variables are measured in each of the subsequent eight quarters (Q1 through Q8) after FVOL measurement. The explanatory variables include FVOL_A, Concavity, and their interaction. Concavity is defined as the quintile rank of the industry-level concavity measure. The reported coefficients are multiplied by 100. The *t*-statistics are reported in parentheses. In Panels B–D, where the dependent variable is a profitability measure, the *t*-statistics are based on Newey–West standard errors with a 12-quarter lag.

Panel A. Dependent variable: stock returns									
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	JT8
Intercept	2.160 (9.15)	2.128 (8.67)	2.012 (8.49)	2.026 (8.07)	2.062 (8.14)	2.108 (8.61)	1.963 (8.32)	1.838 (7.42)	2.055 (8.96)
FVOL	-0.018 (-4.47)	-0.016 (-3.84)	-0.015 (-3.76)	-0.016 (-3.66)	-0.017 (-3.56)	-0.016 (-3.78)	-0.013 (-3.17)	-0.008 (-1.72)	-0.015 (-3.88)
Concavity	-0.162 (-3.65)	-0.149 (-3.10)	-0.133 (-2.86)	-0.133 (-2.63)	-0.137 (-2.60)	-0.152 (-3.02)	-0.115 (-2.44)	-0.085 (-1.69)	-0.139 (-3.27)
FVOL*Concavity	-0.003 (-2.6)	-0.002 (-2.03)	-0.002 (-1.99)	-0.002 (-1.78)	-0.002 (-1.87)	-0.002 (-2.03)	-0.002 (-1.55)	0.000 (-0.20)	-0.002 (-2.16)
Panel B. Dependent variable: gross profitability									
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	JT8
Intercept	18.566 (39.54)	18.190 (39.59)	17.819 (43.07)	17.615 (44.69)	17.368 (43.64)	17.119 (48.67)	16.869 (50.11)	16.540 (45.56)	17.511 (44.94)
FVOL	-0.182 (-29.22)	-0.177 (-29.66)	-0.173 (-30.86)	-0.170 (-31.84)	-0.166 (-33.72)	-0.163 (-34.84)	-0.159 (-37.70)	-0.152 (-33.22)	-0.168 (-34.08)
Concavity	-0.744 (-4.99)	-0.682 (-4.65)	-0.644 (-4.79)	-0.602 (-5.13)	-0.556 (-4.48)	-0.516 (-4.43)	-0.471 (-4.28)	-0.337 (-2.73)	-0.569 (-4.60)
FVOL*Concavity	-0.014 (-4.16)	-0.013 (-4.00)	-0.012 (-4.00)	-0.012 (-3.99)	-0.011 (-3.79)	-0.01 (-3.66)	-0.01 (-3.62)	-0.005 (-1.63)	-0.011 (-3.82)
Panel C. Dependent variable: operating profitability									
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	JT8
Intercept	18.153 (13.50)	16.713 (15.75)	15.503 (19.52)	14.938 (10.81)	13.913 (12.97)	14.938 (13.63)	13.052 (7.57)	13.728 (8.77)	15.117 (17.90)
FVOL	-0.256 (-7.96)	-0.230 (-8.89)	-0.205 (-12.03)	-0.194 (-6.12)	-0.178 (-8.48)	-0.197 (-8.71)	-0.152 (-3.96)	-0.174 (-5.56)	-0.198 (-10.87)
Concavity	-1.938 (-6.00)	-1.731 (-5.54)	-2.274 (-3.54)	-2.107 (-2.28)	-1.348 (-1.68)	-1.775 (-2.56)	-1.685 (-1.89)	-1.886 (-2.14)	-1.843 (-3.41)
FVOL*Concavity	-0.047 (-5.51)	-0.043 (-5.27)	-0.048 (-4.59)	-0.044 (-2.47)	-0.033 (-2.27)	-0.04 (-3.2)	-0.034 (-2.12)	-0.039 (-2.42)	-0.041 (-4.29)
Panel D. Dependent variable: return on equity									
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	JT8
Intercept	11.783 (10.21)	10.292 (11.84)	8.544 (11.63)	9.009 (7.30)	8.100 (9.39)	8.874 (8.96)	7.229 (5.19)	8.536 (6.72)	9.046 (13.04)
FVOL	-0.215 (-7.56)	-0.185 (-8.68)	-0.144 (-8.76)	-0.157 (-5.10)	-0.144 (-7.93)	-0.161 (-7.36)	-0.121 (-3.78)	-0.155 (-5.61)	-0.160 (-10.16)
Concavity	-1.823 (-6.95)	-1.576 (-6.24)	-1.429 (-3.01)	-1.663 (-2.32)	-1.070 (-1.90)	-1.291 (-2.47)	-1.116 (-1.61)	-1.600 (-2.38)	-1.446 (-3.56)
FVOL*Concavity	-0.046 (-6.22)	-0.04 (-5.94)	-0.031 (-3.68)	-0.038 (-2.5)	-0.029 (-2.73)	-0.031 (-2.68)	-0.024 (-1.68)	-0.036 (-2.63)	-0.034 (-4.28)

Table 8. The FVOL-Return Relation Against the Factor Zoo

This table reports results for the FVOL–return relation evaluated against a high-dimensional set of existing factors using the double-selection procedure of Feng et al. (2020). We consider 135 existing factors obtained from Feng et al. The tests are performed using different test assets and factor-selection methods. The factor-selection method in Columns 1–3 is LASSO, and the method in Column 4 is elastic net, which augments the LASSO penalty with a ridge penalty. The test assets in Columns 1 and 4 are 750 3×2 portfolios formed on size and 125 firm characteristics. The test assets in Column 2 are 1,825 5×5 portfolios sorted on size and 73 firm characteristics. In Column 3, the test assets consist of 202 portfolios, including 17 industry portfolios, 35 portfolios sorted by size and net issuance, 25 5×5 portfolios sorted by operating profitability and investment, and 125 5×5 portfolios formed on size and five other anomaly variables. λ_0 is the estimated SDF loading from the second stage of the procedure. t -statistics are reported in parentheses.

(1) LASSO 750 3×2		(2) LASSO 1825 5×5		(3) LASSO 202 Portfolios		(4) Elastic Net 750 3×2	
λ_0	t	λ_0	t	λ_0	t	λ_0	t
66.05	(5.06)	73.00	(5.81)	81.78	(6.00)	53.17	(3.89)

Appendix

A.1. Proof of Proposition 1

For notational convenience, we restate Condition 1) in Proposition 1 as $\partial X_{\tau+1}^*/\partial X_{\tau}^* = c_1 \geq 0$ for all $\tau \geq t+1$, with the understanding that c_1 can vary with τ . We further restate Condition 2) in Proposition 1 here: $\partial m_{\tau+1}/\partial X_{\tau}^* \leq 0$ for all $\tau \geq t+1$.

We first show that firm value V_{t+1} is a strictly increasing and weakly concave function of X_{t+1}^* .

From Eq. (14) and using the Envelope Theorem,

$$\begin{aligned}
 \frac{\partial V_{t+1}}{\partial X_{t+1}^*} &= K_{t+1} + E_{t+1} \left(c_1 m_{t+2} \frac{\partial V_{t+2}}{\partial X_{t+2}^*} \right) \\
 &= K_{t+1} + E_{t+1} \left(m_{t+2} \frac{c_1 \partial X_{t+2}^*}{\partial X_{t+1}^*} K_{t+2} \right) + E_{t+1} \left(c_1^2 m_{t+2} m_{t+3} \frac{\partial V_{t+3}}{\partial X_{t+3}^*} \right) \\
 &= \dots \\
 &= K_{t+1} + \sum_{\tau=2}^{\infty} E_{t+1} (K_{t+\tau} \Pi_{i=2}^{\tau} (c_1 m_{t+i}))
 \end{aligned} \tag{36}$$

Since $K_{t+\tau} > 0$, $m_{t+i} > 0$, and $c_1 \geq 0$, we have,

$$\frac{\partial V_{t+1}}{\partial X_{t+1}^*} > 0 \tag{37}$$

Thus firm value V_{t+1} is strictly increasing in X_{t+1}^* .

Now consider the second-order derivative of V_{t+1} . Starting from the first equality of Eq. (36),

$$\frac{\partial^2 V_{t+1}}{\partial (X_{t+1}^*)^2} = c_1^2 E_{t+1} \left(m_{t+2} \frac{\partial^2 V_{t+2}}{\partial (X_{t+2}^*)^2} \right) + c_1 E_{t+1} \left(\frac{\partial m_{t+2}}{\partial X_{t+1}^*} \frac{\partial V_{t+2}}{\partial X_{t+2}^*} \right) \tag{38}$$

Since $c_1 \geq 0$, $\partial m_{t+2}/\partial X_{t+1}^* \leq 0$, and $\frac{\partial V_{t+2}}{\partial X_{t+2}^*} > 0$ (established above), the second term in the right-hand-side of the above equation is non-positive; i.e., $c_1 E_{t+1} \left(\frac{\partial m_{t+2}}{\partial X_{t+1}^*} \frac{\partial V_{t+2}}{\partial X_{t+2}^*} \right) \leq 0$. Further, since $m_{t+2} > 0$, the first term, $c_1^2 E_{t+1} \left(m_{t+2} \frac{\partial^2 V_{t+2}}{\partial (X_{t+2}^*)^2} \right)$, has the same sign as $\frac{\partial^2 V_{t+2}}{\partial (X_{t+2}^*)^2}$. Hence, if $\frac{\partial^2 V_{t+2}}{\partial (X_{t+2}^*)^2} \leq 0$, then $\frac{\partial^2 V_{t+1}}{\partial (X_{t+1}^*)^2} \leq 0$. Using this result, we can show the concavity of V_{t+1} by backward induction.

Consider a T-period model. At the terminal period T, there is no more investment, and $V_T = K_T X_T^*$. Thus, $\partial V_T/\partial X_T^* = K_T$ and $\partial^2 V_T/\partial (X_T^*)^2 = 0$. Following the above result, this leads to $\partial^2 V_{\tau}/\partial (X_{\tau}^*)^2 \leq 0$ for all $1 \leq \tau < T$. We can extend this result to the case of infinite periods. This establishes that V_{t+1} is weakly concave in X_{t+1}^* .

Now consider the stock return, which can be expressed as

$$R_{t+1}^S = \frac{P_{t+1} + Y_{t+1}}{P_t} = \frac{V_{t+1}}{V_t - Y_t} \quad (39)$$

where P_{t+1} is the ex-payout market value of the stock. $Y_t = X_t^* K_t - \phi_t - I_t$ is the time- t payout.

Since V_{t+1} is strictly increasing and weakly concave in X_{t+1}^* , R_{t+1}^S is increasing and weakly concave in X_{t+1}^* .¹² That is,

$$\begin{aligned} \frac{\partial R_{t+1}^S}{\partial X_{t+1}^*} &> 0 \\ \frac{\partial^2 R_{t+1}^S}{\partial (X_{t+1}^*)^2} &\leq 0 \end{aligned}$$

¹²It is worth noting that while R_{t+1}^S is concave in X_{t+1}^* , it is not necessarily concave in X_t^* . As Eq. (39) shows, X_t^* affects R_{t+1}^S not only via X_{t+1}^* in the numerator, and but also via $V_t - Y_t$ in the denominator.

A.2. Major Items in Balance Sheet and Income Statement

In Table A1, we provide further details on how we select accounting variables to construct the individual $FVOL_k$ measures. We use Compustat standardized financial statements for industrial firms. In Compustat, accounting variables in the financial statements are organized into three levels. First-level variables represent broad categories (e.g., Current Assets), second-level variables are more refined categories (e.g., Cash and Short-term Investments), and third-level variables are the most granular (e.g., Cash). We classify all variables in the top two levels into four groups: (1) production inputs (I); (2) other items (O), including financial-investment items, “Other” items, tax-related items, and production-output-related items; (3) items with insufficient observations in the sample (fewer than 500 observations per quarter) (R); and (4) production-input items that have a correlation above 0.99 with variables in Group 1 (C). Only items in Group I are used to construct the fundamental volatility measures.

A.3. Returns and Alphas for Low- and High-FVOL Portfolios

In Table A2, we report the performance of the Low-FVOL and High-FVOL portfolios during the quarter immediately after portfolio ranking. FVOL is based on each of the 14 individual measures as well as on $FVOL_A$. The table shows that most Low-FVOL portfolios have significantly positive alphas under most factor models, whereas High-FVOL portfolios tend to have significantly negative alphas.

Further, Table A3 reports the performance of the Low-FVOL_A and High-FVOL_A portfolios during each of the eight quarters after the initial ranking. Again, across different factor models, the Low-FVOL_A portfolio tends to have significantly positive alphas in most quarters following FVOL measurement, whereas the High-FVOL_A portfolios tend to have significantly negative alphas.

A.4. Control Variables in Table 5

- **Gross profitability (GP)** revenues minus cost of goods sold, all deflated by total assets.
- **Operating profitability (OP)** revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense, all divided by book equity.
- **Return on equity (ROE)** income before extraordinary items deflated by book equity.
- **Past Profitability (PP)** gross profitability (GP), operating profitability (OP), or return on equity (ROE) in quarter q .
- **Idiosyncratic volatility (IVOL)** the standard deviation of the residuals from a regression of daily stock returns in quarter q on the Fama and French (1993) three-factor model.

- **Book-to-market (BM)** book equity at the end of the fiscal year ending in year y-1, divided by the market capitalization at the end of December of year y-1. Book equity is the stockholders' book equity (Compustat item seq), plus balance sheet deferred taxes and investment tax credit (Compustat item txdite), minus the book value of preferred stocks. We set the book value of preferred stocks to their redemption, liquidation, or par value (Compustat item pstkrv, pstkl, and pstk), depending on their availability. If seq is missing, we measure stockholders' book equity as total assets minus total liabilities (Compustat item at-lt). Market capitalization is the stock price per share times shares outstanding from CRSP at the end of June in year y.
- **Market Capitalization (SIZE)** the stock price per share times shares outstanding from CRSP at the end of June in year y.
- **Negative Profitability (NP)** an indicator that takes a value of 1 if a firm has negative Past Profitability (zero otherwise).
- **-ACCBE** Accruals divided by book equity at the end of the fiscal year ending in year y-1, for firms with negative Accruals (zero otherwise).
- **+ACCBE** Accruals divided by book equity at the end of the fiscal year ending in year y-1, for firms with positive Accruals (zero otherwise).
- **Accruals (Acc)** the change in current assets from the fiscal year ending in year y-2 to fiscal year ending in year y-1, minus the change in cash and cash equivalents, minus the change in current liabilities, plus the change in debt included in current liabilities, plus the change in income taxes payable, minus the depreciation and amortization expense (Compustat item $\Delta\text{act}-\text{check}-\Delta\text{lct}+\Delta\text{dlc}+\Delta\text{txp}-\text{dp}$).
- **Asset growth rate (AG)** the percentage change in total assets from fiscal year ending in calendar year y-2 to fiscal year ending in calendar year y-1.
- **Dividends-to-book (DIVBE)** total dividends divided by book equity at the end of the fiscal year ending in year y-1 (compustat item dvt, or dv, depending on their availability).
- **No Dividend (NODIV)** an indicator that takes value of 1 if a firm pays no dividends during fiscal year ending in year y-1 (zero otherwise).
- **Ret_1yr** the 12-month cumulative stock return at end of fiscal year ending in year y-1.
- **Ret_23yr** the 24-month cumulative stock return from fiscal year ending in year y-3 to y-2.
- **Probability of Default on Debt (O_Score)** Estimated from the probit regression model of Ohlson (1980) at the end of the fiscal year ending in year y-1.
- **Composite index of firm strength (F_Score)** the index defined as in Piotroski(2000) at the end of the fiscal year ending in year y-1.

A.5. Control Variables in Table 6

- **Idiosyncratic volatility (IVOL)** the standard deviation of the residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) three-factor model.
- **Skewness (Skew)** the skewness of daily stock returns in month t-1.
- **Coskewness (Coskew)** the coefficient from a regression of squared daily individual stock returns in month t-1 on market daily returns.
- **Average variance beta (AvgVar β)** a stock's exposure to the innovation in average stock variance in month t-1. The exposure is estimated by regressing monthly excess returns on the Fama and French (1993) three-factor model, innovation in average stock variance, and innovation in average stock correlation using 60-month rolling windows. Average stock correlation is the value-weighted average of pairwise correlations of daily stock returns during each month for all stocks. Average stock variance is the value-weighted average of variance of daily stock returns during each month for all stocks.
- **One-month reversal effect (Lagret)** the returns for individual stocks in month t-1.
- **Illiquidity (Illiq)** the average of daily absolute returns divided by daily dollar trading volume in month t-1.
- **Maximum daily return (Maxret)** the maximum of daily stock returns in month t-1.
- **Zero returns (Zeroret)** the fraction of trading days with a zero return in month t-1.
- **Size** the market equity at the end of the most recent June.
- **Book-to-Market (BM)** book equity at the end of the fiscal year ending in year y-1, divided by the market capitalization at the end of December of year y-1. Book equity is the stockholders' book equity (Compustat item seq), plus balance sheet deferred taxes and investment tax credit (Compustat item txdlite), minus the book value of preferred stocks. We set the book value of preferred stocks to their redemption, liquidation, or par value (Compustat item pstkrv, pstkl, and pstk), depending on their availability. If seq is missing, we measure stockholders' book equity as total assets minus total liabilities (Compustat item at and lt). Market capitalization is the stock price per share times shares outstanding from CRSP at the end of June in year y.
- **Operating profitability (OP)** revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense (Compustat item revt, cogs, xsga, and xint) at the end of the fiscal year ending in year y-1, all divided by book equity for the fiscal year ending in year y-2.

- **Asset growth rate (AG)** the percentage change in total assets from fiscal year ending in calendar year y-2 to fiscal year ending in calendar year y-1.
- **Accruals (Acc)** the change in current assets from the fiscal year ending in year y-2 to fiscal year ending in year y-1, minus the change in cash and cash equivalents, minus the change in current liabilities, plus the change in debt included in current liabilities, plus the change in income taxes payable, minus the depreciation and amortization expense (Compustat item $\Delta\text{act}-\text{chech}-\Delta\text{lct}+\Delta\text{dlc}+\Delta\text{txp}-\text{dp}$), all divided by the average of total assets of the fiscal year ending in year y-2 and y-1.
- **Standardized unexpected earnings (SUE)** the quarterly unexpected earnings (UE) divided by the standard deviation of UE a quarter after the most recent rdq. UE is the reported quarterly earnings per share (Compustat item epsfxq) minus EPS reported four quarters ago. The standard deviation is calculated from UE over the past eight quarters or a minimum of four quarters.

A.6. Explaining the IVOL-Return Relation

Table A4 reports Fama–MacBeth regression results linking the IVOL–return relation to the IVOL–profitability relation. The dependent variable is the monthly stock return in the quarter following IVOL measurement. The explanatory variables include IVOL and one of three profitability measures—gross profitability, operating profitability, or return on equity. These profitability measures are constructed from quarterly financial-statement data available for the quarter contemporaneous with the dependent variable (stock returns). The table shows that, without controlling for contemporaneous profitability (Column (1)), the coefficient on IVOL is significantly negative. After controlling for gross profitability, the coefficient on IVOL remains significantly negative. However, once operating profitability or return on equity is included as a control, the coefficient on IVOL is no longer statistically significant.

Table A1. Accounting Variables For Fundamental Volatility Measures

This table lists Compustat balance-sheet and income-statement variables at the top two levels and categorizes them into four groups: (1) production inputs (I); (2) other items (O), including financial-investment items, “Other” items, tax-related items, and production-output-related items; (3) items with insufficient observations in the sample (R); and (4) production-input items that have a correlation greater than 0.99 with variables in Group 1 (C). Only items in Group I are used to measure fundamental volatility.

Balance Sheet			
Assets		Liabilities and Equity	
Current Assets		Current Liabilities	
Cash and Short-Term Investments (cheq)	O	Debt in Current Liabilities (dlcq)	I
Receivables - Total (rectq)	I	Accounts Payable/Creditors - Trade (apq)	I
Inventories - Total (invtq)	I	Income Taxes Payable (txpq)	O
Current Assets - Other - Total (acoq)	O	Current Liabilities - Other (lcoq)	O
Current Assets - Total (acq)	I	Current Liabilities - Total (lctq)	I
Property Plant and Equipment - Total (Net) (ppentq)	I	Long-Term Debt - Total (dlttq)	I
Assets - Other - Total (aoq)	O	Deferred Taxes and Investment Tax Credit (txditcq)	O
Assets - Total (atq)	I	Liabilities - Other (loq)	O
		Liabilities - Total (ltq)	I
		Noncontrolling Interest - Redeemable - Balance Sheet (mibq)	R
		Shareholders' Equity	
		Preferred/Preference Stock (Capital) - Total (pstkq)	R
		Common/Ordinary Equity - Total (ceqq)	C
		Stockholders Equity - Parent - Total (seqq)	I
		Noncontrolling Interest - Nonredeemable (mibnq)	R
		Stockholders Equity - Total (teqq)	R
		Liabilities and Stockholders Equity - Total (lseq)	C

Table A1. (Continued)

Income Statement	
Sales/Turnover (Net) (saleq)	O
Operating Expense (xoprq)	I
Cost of Goods Sold (cogsq)	I
Selling, General and Administrative Expenses (xsgaq)	I
Operating Income Before Depreciation (oibdpq)	O
Depreciation and Amortization - Total (dpq)	O
Operating Income After Depreciation (oiadpq)	O
Interest Expense (xintq)	O
Nonoperating Income (Expense) - Total (nopi)	O
Special Items (spiq)	O
Pretax Income (piq)	O
Income Taxes - Total (txtq)	O
Income Before Extraordinary Items and Noncontrolling Interests (ibmiiq)	O
Noncontrolling Interest - Income Account (miiq)	O
Income Before Extraordinary Items (ibq)	O
Dividends - Preferred/Preference (dvpq)	O
Income Before Extraordinary Items - Available for Common (ibcomq)	O
Common Stock Equivalents - Dollar Savings (cstkeq)	O
Income Before Extraordinary Items - Adjusted for Common Stock Equivalents (ibadjq)	O
Extraordinary Items and Discontinued Operations (xidoq)	O
Extraordinary Items (xiq)	O
Discontinued Operations (doq)	O
Net Income (Loss) (niq)	O

Table A2. Performance of FVOL Portfolios at Short Horizon

This table reports the performance of the Low-FVOL_k and High-FVOL_k portfolios during the three months after portfolio formation. Performance is measured by average monthly returns (“Ret”), and by the monthly alphas based on CAPM, the three-factor, four-factor, five-factor, and q-factor models (labeled as “CAPM”, “FF3”, “FF4”, “FF5”, and “q4” respectively). Each quarter, stocks are sorted into deciles based on FVOL_k. The Low-FVOL (High-FVOL) portfolio consists of stocks in the bottom (top) FVOL decile. Portfolios are value-weighted. Returns and alphas are expressed in percentage points (%). *t*-statistics are reported in parentheses.

FVOL	Ret	Low					Ret	High				
		CAPM α	FF3 α	FF4 α	FF5 α	q4 α		CAPM α	FF3 α	FF4 α	FF5 α	q4 α
atq	0.84	0.23 (2.37)	0.25 (2.52)	0.24 (2.43)	0.07 (0.75)	0.04 (0.42)	0.18	-0.73 (-5.29)	-0.65 (-5.56)	-0.62 (-5.17)	-0.31 (-2.86)	-0.30 (-2.43)
actq	0.77	0.17 (1.74)	0.16 (1.63)	0.14 (1.49)	-0.05 (-0.53)	-0.07 (-0.70)	0.31	-0.67 (-3.35)	-0.50 (-3.48)	-0.48 (-3.28)	0.01 (0.11)	0.00 (0.00)
rectq	0.84	0.19 (1.90)	0.22 (2.16)	0.23 (2.17)	0.06 (0.56)	0.05 (0.49)	0.26	-0.68 (-4.24)	-0.61 (-4.56)	-0.59 (-4.28)	-0.30 (-2.36)	-0.28 (-1.95)
invttq	0.94	0.18 (1.37)	0.31 (2.93)	0.34 (3.12)	0.50 (4.59)	0.53 (4.35)	0.35	-0.60 (-3.90)	-0.54 (-4.70)	-0.50 (-4.27)	-0.29 (-2.66)	-0.26 (-2.07)
ppentq	0.86	0.14 (1.37)	0.19 (1.93)	0.19 (1.95)	0.16 (1.71)	0.14 (1.36)	0.29	-0.51 (-3.91)	-0.56 (-4.47)	-0.58 (-4.60)	-0.49 (-3.87)	-0.46 (-3.53)
ltq	0.87	0.21 (2.10)	0.27 (2.73)	0.25 (2.51)	0.21 (2.15)	0.19 (1.87)	0.32	-0.54 (-4.45)	-0.51 (-4.81)	-0.49 (-4.53)	-0.29 (-2.81)	-0.26 (-2.31)
lctq	0.93	0.27 (2.88)	0.31 (3.41)	0.29 (3.14)	0.24 (2.66)	0.23 (2.44)	0.22	-0.63 (-4.99)	-0.56 (-5.11)	-0.57 (-5.07)	-0.34 (-3.17)	-0.35 (-2.89)
dlcq	0.73	-0.01 (-0.10)	0.12 (1.04)	0.22 (1.89)	0.29 (2.52)	0.35 (2.78)	0.44	-0.24 (-2.54)	-0.24 (-2.76)	-0.25 (-2.90)	-0.17 (-1.94)	-0.16 (-1.73)
apq	0.77	0.07 (0.80)	0.13 (1.56)	0.12 (1.45)	0.08 (0.99)	0.09 (1.07)	0.38	-0.51 (-3.69)	-0.49 (-4.03)	-0.48 (-3.90)	-0.32 (-2.61)	-0.24 (-1.88)
dlttq	0.86	0.11 (0.79)	0.25 (2.10)	0.31 (2.57)	0.44 (3.64)	0.46 (3.52)	0.39	-0.39 (-3.45)	-0.34 (-3.41)	-0.34 (-3.34)	-0.18 (-1.81)	-0.16 (-1.49)
seqq	0.79	0.22 (2.01)	0.21 (1.84)	0.19 (1.69)	0.02 (0.18)	-0.02 (-0.15)	0.12	-0.74 (-4.94)	-0.61 (-4.89)	-0.57 (-4.52)	-0.22 (-2.01)	-0.22 (-1.67)
xoprq	0.92	0.26 (3.30)	0.32 (4.08)	0.31 (3.92)	0.21 (2.73)	0.22 (2.71)	0.14	-0.80 (-4.91)	-0.75 (-5.92)	-0.71 (-5.52)	-0.36 (-3.16)	-0.32 (-2.44)
cogsq	0.89	0.24% (3.04)	0.30 (4.05)	0.26 (3.53)	0.21 (2.90)	0.21 (2.70)	0.27	-0.64 (-4.21)	-0.62 (-5.04)	-0.58 (-4.66)	-0.33 (-2.80)	-0.32 (-2.48)
xsgaq	0.71	0.13 (1.71)	0.13 (1.65)	0.07 (0.89)	0.07 (0.89)	0.07 (0.86)	0.31	-0.47 (-3.06)	-0.30 (-2.39)	-0.26 (-2.02)	0.05 (0.40)	0.07 (0.56)
FVOL _A	0.92	0.28 (2.89)	0.31 (3.23)	0.30 (3.11)	0.18 (1.98)	0.17 (1.78)	-0.01	-0.97 (-5.90)	-0.90 (-6.55)	-0.85 (-6.12)	-0.54 (-4.25)	-0.49 (-3.45)

Table A3. Performance of FVOL Portfolios over Long Horizon

This table reports the performance of Low-FVOL_A and High-FVOL_A portfolios during each of the eight quarters (Q1 through Q8) after portfolio formation. The row labeled “JT8” summarizes the performance over 8 quarters using the non-overlapping portfolio approach of Jegadeesh and Titman (1993). Performance is measured by average monthly returns (“Ret”), and the monthly alphas based on CAPM, the three-factor, four-factor, five-factor, and q-factor models (labeled as “CAPM”, “FF3”, “FF4”, “FF5”, and “q4” respectively). Each quarter, stocks are sorted into deciles based on FVOL_A. The Low-FVOL_A (High-FVOL_A) portfolio consists of stocks in the bottom (top) FVOL_A decile. Portfolios are value-weighted. Returns and alphas are expressed in percentage points (%), and *t*-statistics are reported in parentheses.

Quarter	Ret	Low					Ret	CAPM	High				
		CAPM	FF3	FF4	FF5	q4			FF3	FF4	FF5	q4	
Q1	0.92	0.28 (2.89)	0.31 (3.23)	0.30 (3.11)	0.18 (1.98)	0.17 (1.78)	-0.01	-0.97 (-5.90)	-0.90 (-6.55)	-0.85 (-6.12)	-0.54 (-4.25)	-0.49 (-3.45)	
Q2	0.91	0.26 (2.74)	0.29 (3.04)	0.28 (2.92)	0.16 (1.75)	0.15 (1.62)	-0.05	-1.04 (-6.40)	-0.96 (-6.99)	-0.87 (-6.29)	-0.62 (-4.82)	-0.55 (-3.91)	
Q3	0.90	0.25 (2.69)	0.28 (3.05)	0.28 (2.99)	0.17 (1.90)	0.18 (1.91)	0.02	-0.98 (-6.16)	-0.90 (-6.53)	-0.78 (-5.72)	-0.57 (-4.34)	-0.50 (-3.52)	
Q4	0.91	0.24 (2.51)	0.27 (2.87)	0.27 (2.81)	0.18 (1.89)	0.19 (1.91)	0.07	-0.92 (-6.04)	-0.83 (-6.42)	-0.73 (-5.65)	-0.54 (-4.32)	-0.47 (-3.46)	
Q5	0.90	0.24 (2.48)	0.28 (2.84)	0.28 (2.79)	0.20 (2.02)	0.20 (2.05)	0.13	-0.84 (-5.46)	-0.75 (-5.76)	-0.67 (-5.11)	-0.47 (-3.75)	-0.42 (-3.08)	
Q6	0.92	0.27 (2.87)	0.31 (3.24)	0.29 (3.09)	0.22 (2.39)	0.22 (2.29)	0.27	-0.66 (-4.30)	-0.56 (-4.34)	-0.53 (-4.01)	-0.33 (-2.60)	-0.29 (-2.06)	
Q7	0.99	0.32 (3.37)	0.36 (3.79)	0.35 (3.63)	0.27 (2.80)	0.26 (2.68)	0.25	-0.68 (-4.42)	-0.61 (-4.56)	-0.61 (-4.49)	-0.37 (-2.84)	-0.33 (-2.36)	
Q8	0.91	0.26 (2.63)	0.29 (3.05)	0.28 (2.87)	0.21 (2.17)	0.22 (2.17)	0.21	-0.70 (-4.86)	-0.64 (-5.02)	-0.64 (-4.94)	-0.43 (-3.44)	-0.44 (-3.23)	
JT8	0.92	0.28 (3.07)	0.31 (3.45)	0.30 (3.32)	0.21 (2.33)	0.20 (2.25)	0.11	-0.83 (-5.88)	-0.77 (-6.65)	-0.72 (-6.11)	-0.49 (-4.46)	-0.44 (-3.62)	

Table A4. Decomposing the IVOL-Return Relation via Multivariate Regressions

This table reports results from Fama–MacBeth regressions of monthly stock returns on idiosyncratic volatility (IVOL) and profitability. IVOL is measured as the standard deviation of residuals from regressing a stock’s daily returns within a quarter on the daily Fama–French three factors. The dependent variable is the monthly stock return in each of the three months after IVOL is measured. Profitability is measured by gross profitability (GP), operating profitability (OP), and return on equity (ROE). These profitability measures are computed for the quarter after IVOL measurement, that is, for the quarter contemporaneous with the dependent variable (stock returns). Cross-sectional regressions are run each month. Column (1) includes IVOL as the only explanatory variable. Columns (2)–(4) additionally include GP, OP, and ROE, respectively, as explanatory variables. Reported coefficients are multiplied by 100. *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
	Profitability Measure			
		GP	OP	ROE
Intercept	1.375 (8.33)	1.394 (8.44)	1.203 (7.37)	1.164 (7.06)
IVOL	-0.006 (-2.29)	-0.006 (-2.47)	-0.002 (-0.92)	-0.001 (-0.58)
Profitability		0.548 (14.58)	0.755 (17.45)	0.863 (19.25)