Does an Option-based Discount Rate Predict Stock Returns?*

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August 17, 2024

Abstract

We estimate the short-term discount rate from the options written on the S&P 500 index via the put-call parity. This estimated discount rate predicts average stock returns significantly both in-sample and out-of-sample. Cross-sectionally, stocks with higher exposure to the short discount rate earn higher average returns; they significantly outperform the low-exposure stocks by 0.49% (0.72%) per month under equal (value) weights. Using the demand system approach, we find that long-term investors tend to hold stocks with low (negative) exposure to the short discount rate. In contrast, short-term investors outweigh this risk relative to the household and mid-term investors.

JEL Classifications: G12, G13
Keywords: Short-term Discount Rate, Implied Volatility, Return Predictability, ICAPM, Demand System.

*This paper was originally circulated as "Slope Beta and Cross-Sectional Stock Returns." For helpful comments, we thank Kai Li (discussant at the 2022 Chinese Finance Annual Meeting), Zhiyao Chen (discussant at the 2023 China International Conference in Finance), Fuwei Jiang (discussant at the 2023 China Derivatives Youth Forum), Sangik Seok (discussant at the 2023 Annual Conference of the Asia-Pacific Association of Derivatives), Martijn Boons, Jeffrey Callen, Shuaiqi Li, Alessandro Melone, Zhengyang Xu, and seminar participants at City University of Hong Kong. We take full responsibility for any remaining errors in the paper.

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1 Introduction

The discount rate plays a crucial role in the decision-making process by investors, financial analysts, corporate managers, and policymakers. Thus, matching the variation in the discount rate becomes one of the key criteria in evaluating an asset pricing model. However, it has been challenging to determine the price of the discount rate in the cross-section of stocks. Lacking a proper measure of the discount rate, the literature uses the realized return as a proxy, which has a low signal-to-noise ratio. Consequently, the cross-sectional result is typically in-sample, often not significantly different from zero, and sensitive to the choice of predictors for the future return.

This paper presents a novel method that incorporates data from the derivatives market. Taking advantage of the forward-looking nature of options, we start by constructing a new measure of the discount rate that can be observed in real-time, thus allowing us to estimate the exposure to the discount rate news at the individual stock level (rather than portfolio level) with a short rolling window (rather than full-sample data). We then proceed with the standard asset pricing tests that reveal a significant and robust positive price of risk for the discount rate news.

Specifically, our measure is motivated by the recent equity term structure literature (van Binsbergen, Brandt and Koijen, 2012);[1] they rely on the put-call parity to infer the present values of dividend strips, enabling them to estimate sample-average short-term discount rates. Instead of investigating the average returns, we use the put-call parity to approximate the conditional short-term discount rate for each maturity of options (written on the S&P 500 index), linking the short-term discount rate directly to the at-the-money put-call implied volatility ratio. We then use this ratio for different option maturities to estimate a mean conditional discount rate over the option maturities via a regression. We call the slope of this regression *spc* and the resulting conditional short-term discount rate r^{spc}.

The approximations are also based on historical averages of dividend growth rate, dividend yield, and volatility before the start of our sample period. This allows us to observe r^{spc} in real time and measure the cross-sectional exposure to discount rate shock in a short rolling window, which is crucial to our analysis. However, like the common low-frequency measures of discount rate such as the dividend yield, r^{spc} is also influenced by factors not directly related to the discount rate

[1] Other papers that also use options (index or stocks) to infer discount rates or risk premiums include Martin (2017), Callen and Lyle (2020), and Ulrich, Florig and Seehuber (2023), among others.

such as dividend growth rate or volatility. Therefore, we begin our empirical analysis by verifying the predictability in the time series. We find that the difference between r^{spc} and risk-free rate r^f significantly predicts future stock market excess return, even when controlling for other time series predictors, including the market expected return bound (Martin, 2017), the cross-sectional average of implied volatility spread (Han and Li, 2021), the implied volatility skew (Atilgan, Bali and Demirtas, 2015) as well as spread and ratio, the predictors in Welch and Goyal (2008), and the variance risk premium (Bollerslev, Tauchen and Zhou, 2009).

In the predictive regression, while we strongly reject no predictability, we cannot reject the hypothesis that the coefficient on $r^{spc} - r^f$ is one and the intercept is zero. Consequently, if we predict the future one-year market excess return using $r^{spc} - r^f$, we achieve an estimation-free (out-of-sample) R-squared of 10.12%, comparable to the in-sample R-squared. This result might seem surprising as r^{spc} is designed to measure the discount rate for short-term dividend claim, not the stock. However, this finding is consistent with the empirical evidence that the equity term structure is, on average, approximately flat, even though the shape varies significantly over time (Bansal, Miller, Song and Yaron, 2021; Gormsen, 2021).

The result is also robust to the parameter choice of dividend growth rate, dividend yield, and volatility, which are needed to transform *spc* into r^{spc}. In particular, the out-of-sample performance improves significantly if we use up-to-date volatility. However, we choose to take a conservative approach by calibrating the values to the historical average. Therefore, the variation of r^{spc} is completely attributable to *spc*.

We then study the price of risk of r^{spc} in the cross-section of stocks. As r^{spc} can be estimated at daily frequency, we measure the sensitivity to the discount rate by regressing the stock return on r^{spc} using the past 12-month daily data. The resulting coefficient is named β^{spc}. In the univariate portfolio analysis, equal-weighted (value-weighted) portfolios sorted by β^{spc} generate a monthly high-minus-low return spread of 0.49% (0.72%) with t-statistics of 2.81 (3.94), which translates to an annual spread of 5.88% (8.64%). Moreover, even after adjusting for various factor models such as CAPM (Sharpe, 1964; Lintner, 1965), Fama-French (1992; 2015) (three-factor, five-factor, and six-factor) models, Carhart (1997) four-factor model, and the Q5 model in Hou, Mo, Xue and Zhang (2021), the alphas remain statistically and economically significant. The results indicate a positive price of short-term discount rate risk.

We also perform bivariate portfolio analysis and Fama-Macbeth regressions, controlling for various stock characteristics such as CAPM beta, volatility beta, size, book-to-market ratio, momentum, reversal, illiquidity, idiosyncratic volatility, asset growth, and profitability. However, these variables do not explain the β^{spc} effect. The predictive ability is also not limited to any specific period, as demonstrated by tracking the return of β^{spc}-sorted strategy over time.

We conduct multiple tests to ensure the reliability of our finding. First, our results remain consistent when using different methods to construct r^{spc}. In the main analysis, we use put-call implied volatility ratio to mitigate the volatility level effect, but our results are robust to regressing put-call implied volatility spread (instead of ratio) on maturity. Furthermore, to exactly match our theoretical analysis, we also use put and call implied volatility at the same strike from interpolation, instead of the implied volatility at delta -0.5 and 0.5. Additionally, we remove the very short and very long maturities for liquidity reasons. The results indicate that the time-series predictability and cross-sectional risk premium are robust to these alternative r^{spc}.

Second, we demonstrate that the result is robust to how to estimate the slope beta β^{spc}. In the main analysis, when calculating β^{spc}, we use the level of r^{spc} due to its low persistence. We conduct a robustness test using the innovation obtained from an AR(1) model with full sample data or rolling or recursive window data to avoid look-ahead bias. We also experiment with different sets of factor controls in the estimation. Across the different specifications, the cross-sectional risk premium is consistently positive.

Our final robust test explores an alternative interpretation of the main results. It is possible that the slope of the put-call ratio changes due to informed trading. For example, if there is a high demand for hedging future crashes, this could increase the implied volatility of long maturity put options. In this case, *spc* (r^{spc}) negatively (positively) predicts future return. To distinguish between our explanation and this informed trading argument, we turn to individual stock options. If the informed trading argument is true, it would also apply to the options on individual stocks, and the result should be stronger as informed trading is more prevalent in individual stock options. However, our discount rate hypothesis does not apply to individual stock options because they are more prone to short-term dividend growth and other corporate events. After constructing spc_i from individual stock options, we find that it does not provide any additional information after controlling for other option-based predictors in the literature. However, β^{spc} consistently exhibits a significantly predictive ability, which helps us to rule out the informed trading interpretation.

These results show strong and robust evidence that r^{spc} is positively priced in the cross-section of stock returns. In Merton's (1973) terminology, the result means that the representative investor wants to hedge the unfavorable shift of investment opportunity. In the context of this paper, the "unfavorable shift" means a decrease in the expected future return or low r^{spc}. Consequently, investors may weigh less on stocks that perform poorly during such a shift, i.e., stocks with positive β^{spc}, leading to a higher required return. Conversely, investors with consumption positively correlated with this short-term discount rate risk may outweigh their portfolio on these stocks. Specifically, long-term and short-term investors may have different demands on stocks sensitive to the short-term discount rate risk.

To account for the difference among investors, we use various criteria, including the data provided by Brian Bushee (Bushee, 1998; Bushee and Noe, 2000; Bushee, 2001) and the churn rate method (Gaspar, Massa and Matos, 2005; Yan and Zhang, 2009), to differentiate between long-term and short-term investors. Using the demand system approach (Koijen and Yogo, 2019), we discover that β^{spc} negatively impacts the weight of a stock in long-term investors' portfolios. We also find that the loading of portfolio weight on β^{spc} increases as the investment horizon shortens, consistent with Merton's (1973) ICAPM.

This study primarily examines the price of discount rate risk. Campbell and Vuolteenaho (2004) use a vector autoregression (VAR) approach[2] to extract the discount rate from stock returns. Kozak and Santosh (2020) have developed a novel method that directly estimates covariance with the discount rate, uncovering a negative risk price. Their approach, requiring future realized returns from extensive time series and utilizing full-sample information, is applicable to portfolios. In contrast, our methodology employs historical data and extends applicability to both portfolios and individual stocks, unveiling a significant and positive risk price. This finding aligns with Badidi, Boons and Frehen (2022), who analyzed returns surrounding macroeconomic announcement days.

Moreover, our work enriches the vast research on option-implied information (Christoffersen, Jacobs and Chang, 2013). It intersects primarily with two streams of literature. First, it augments the literature on the put-call implied volatility spread by investigating term structure information.

[2] The VAR approach is also employed in Campbell (1991, 1996); Bansal, Kiku, Shaliastovich and Yaron (2014); Campbell, Giglio, Polk and Turley (2018).

Cremers and Weinbaum (2010) find that the put-call implied volatility spread, derived from individual stock options, predicts stock returns cross-sectionally, attributing this to informed trading in the options market. Conversely, Bali and Hovakimian (2009) and Yan (2011) observe similar predictive power but link it to its proxy for jump risk. Our focus diverges to term structure information, employing the index option's put-call implied volatility ratio (*spc*) as both a time-series predictor and a systematic risk across the cross-section.

Second, this paper relates to the literature on the term structure of implied volatility, which has been shown to forecast future shifts in the short-term implied volatility (Mixon, 2007), cross-sectional option returns (Vasquez, 2017), and the returns of variance-related assets (Johnson, 2017). However, there is no evidence of its predictive ability for aggregate stock market returns. Our study, examining the term structure of the put-call implied volatility ratio, identifies it as an effective time-series predictor. Additionally, in the cross-sectional analysis, Xie (2014) investigates whether the term structure of implied volatility constitutes a priced risk across stocks and finds a correlation between individual stocks' exposure to volatility term structure changes and future returns, albeit with limited predictability. Distinctively, we derive the linkage between the short-term discount rate with the put-call implied volatility ratio and show that our slope of the put-call implied volatility ratio is a significantly stronger predictor of returns cross-sectionally.

2 r^{spc} and Stock Market Return

2.1 Short-Term Rate and Implied Volatilities

Our analysis is motivated by the equity term structure literature (van Binsbergen, Brandt and Koijen, 2012), which relies on put-call parity to infer the discount rate for short maturity dividends. In the absence of arbitrage, for an index option with European style, the following put-call parity always holds:

$$S_t - PV_t^T(D) + p_{t,\tau}(K) = c_{t,\tau}(K) + e^{-r^f \tau}K, \tag{1}$$

where S_t is the stock price at time t, K is the strike price, $PV_t^T(D)$ is the present value of dividends between t and T, $p_{t,\tau}(K)$ and $c_{t,\tau}(K)$ are the prices of put and call option at time t with strike K and maturity $\tau = T - t$, and r^f is the risk-free rate.

When the dividend yield q_t is constant between t and T, the put-call parity becomes

$$e^{-q_t\tau}S_t + p_{t,\tau}(K) = c_{t,\tau}(K) + e^{-r^f\tau}K \tag{2}$$

with $PV_t^T(D) = (1 - e^{-q_t\tau})S_t$. Then, from the textbook (e.g., Hull, 2017, 10th edition, p430), the Black-Scholes (1973) implied volatility of put and call options with the same strike and maturity would be the same. However, this is not true when the dividend yield is stochastic.

Let $\sigma^p_{t,\tau}$ and $\sigma^c_{t,\tau}$ be the Black-Scholes (1973) implied volatilities of put and call with strike $K^* = S_t e^{(r^f - q_t)\tau}$ and maturity τ, where $q_t = D_t/S_t$ is the dividend yield at time t. Then, equation (1) shows

$$\begin{aligned} PV_t^T(D) - (1 - e^{-q_t\tau})S_t &= p_{t,\tau}(K^*) - c_{t,\tau}(K^*) \\ &\approx e^{-q_t\tau}S_t N'(0)(\sigma^p_{t,\tau} - \sigma^c_{t,\tau})\sqrt{\tau}, \end{aligned} \tag{3}$$

where we use the approximate pricing formula for the at-the-money options.[3] On the other hand, we can rewrite the left side by discounting future dividends with the average discount rate $r_{t,\tau}$ and dividend growth rate $g_{t,\tau}$ over the options' life

$$\begin{aligned} PV_t^T(D) - (1 - e^{-q_t\tau})S_t &= \int_t^T e^{-r_{t,\tau}(s-t)} D_s\, ds - (1 - e^{-q_t\tau})S_t \\ &= q_t S_t \frac{1 - e^{-(r_{t,\tau} - g_{t,\tau})\tau}}{r_{t,\tau} - g_{t,\tau}} - (1 - e^{-q_t\tau})S_t \\ &\approx -\frac{1}{2} q_t S_t (r_{t,\tau} - g_{t,\tau} - q_t)\tau^2, \end{aligned} \tag{4}$$

where we use $D_s = D_t e^{g_{t,\tau}(s-t)} = q_t S_t e^{g_{t,\tau}(s-t)}$ with $g_{t,\tau}$ as the expected dividend growth rate and apply second-order Taylor expansion to the exponential function in Equation (4). These equations show

$$e^{-q_t\tau}S_t N'(0)(\sigma^p_{t,\tau} - \sigma^c_{t,\tau})\sqrt{\tau} \approx -\frac{1}{2} q_t S_t (r_{t,\tau} - g_{t,\tau} - q_t)\tau^2,$$

[3] The Black-Scholes (1973) option pricing formula for call option is $c(S, K, \sigma, r^f, \tau, q) = e^{-q\tau}SN(d_1) - e^{-r^f\tau}KN(d_2)$, where $d_1 = \frac{\ln(S/K) + (r^f - q + 0.5\sigma^2)\tau}{\sigma\sqrt{\tau}}$, $d_2 = d_1 - \sigma\sqrt{\tau}$, and $N(\cdot)$ is the cumulative probability of standard normal distribution. For at-the-money option defined as $K^* = Se^{(r^f - q)\tau}$, we have $c_{t,\tau}(K^*) = e^{-q\tau}S_t(N(0.5\sigma^c_{t,\tau}\sqrt{\tau}) - N(-0.5\sigma^c_{t,\tau}\sqrt{\tau})) \approx e^{-q\tau}S_t N'(0)\sigma^c_{t,\tau}\sqrt{\tau}$ by applying the first-order Taylor expansion to $N(\cdot)$. Similarly, we can get the approximate pricing formula for at-the-money put option as $p_{t,\tau}(K^*) \approx e^{-q\tau}S_t N'(0)\sigma^p_{t,\tau}\sqrt{\tau}$.

which can be simplified as

$$r_{t,\tau} \approx g_{t,\tau} + q_t - \frac{2N'(0)e^{-q_t\tau}}{q_t}\frac{\sigma^p_{t,\tau} - \sigma^c_{t,\tau}}{\tau\sqrt{\tau}}. \tag{5}$$

This equation offers an estimate of the short-term discount rate by the implied volatilities, $\frac{\sigma^p_{t,\tau}-\sigma^c_{t,\tau}}{\tau\sqrt{\tau}}$. To reduce the estimation error, we can use all maturities (τ), by regressing $(\sigma^p_{t,\tau} - \sigma^c_{t,\tau})$ on $\tau\sqrt{\tau}$ at each day t, to estimate an average discount rate over the life of all options. To reduce effect caused by the transitory variation in volatility, we propose to regress the implied volatility ratio $\frac{\sigma^p_{t,\tau}-\sigma^c_{t,\tau}}{\sigma^c_{t,\tau}}$ on $\tau\sqrt{\tau}$ instead. Then substituting the resulting slope, named as spc_t, in Equation (5) yields

$$r_{t,\tau} \approx g_{t,\tau} + q_t - \frac{2N'(0)e^{-q_t\tau}\sigma^c_t}{q_t} spc_t. \tag{6}$$

Given this estimate, one can propose measure of the discount rate based on any combination of the variables on the right-hand side. In this paper, we focus on spc_t and fix the rest. We define

$$r^{spc}_t \equiv \bar{g} + \bar{q} - \frac{2N'(0)\bar{\sigma}}{\bar{q}} spc_t \tag{7}$$

with $N'(0) \approx 0.4$, $e^{-q_t\tau} \approx 1$, and $\bar{g}$, $\bar{q}$, and $\bar{\sigma}$ calibrated to the historical averages before January 1996, when spc_t becomes available. As shown later, this specification is robust to other variations that use time-varying variables.

2.2 Construction of r^{spc}_t

To implement the estimation in Equation (7), we start by calculating

$$pc^\tau_t = \frac{\sigma^{(-0.5put)}_{t,\tau} - \sigma^{(0.5call)}_{t,\tau}}{\sigma^{(0.5call)}_{t,\tau}} \tag{8}$$

as the ratio of the implied volatility of put and call options at date t, with $\sigma^{(-0.5put)}_{t,\tau}$ ($\sigma^{(0.5call)}_{t,\tau}$) representing the implied volatility of the put (call) option with delta -0.5 (0.5) and maturity τ for the S&P 500 index options. These values can be obtained from the Volatility Surface in OptionMetrics. While the strike prices at deltas 0.5 and -0.5 do not precisely match the at-the-money strike in our theoretical model, they have the advantages of directly mapping to the Volatility Surface and avoiding additional estimations. In the robustness tests, we use alternative definitions of at-the-money option through strike price $K = Se^{(r^f - q)\tau}$.

Next, at each day t, we run an OLS regression of pc_t^τ on $\tau\sqrt{\tau}$, utilizing all available maturities in the Volatility Surface (T=10, 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 days), to obtain the slope spc_t

$$pc_t^\tau = \text{Intercept}_t + spc_t \times \tau\sqrt{\tau} + \varepsilon_t^\tau, \tag{9}$$

where $\tau = \frac{T}{365}$ represents the maturity measured in years. In the robustness tests, we remove very short and very long maturities for liquidity reasons.

Finally, the measure of short-term discount rate r_t^{spc} is calculated as

$$r_t^{spc} = 3.18\% + 4.93\% - \frac{0.8 \times 20.47\%}{4.93\%} spc_t \tag{10}$$

based on the historical average of g_t, q_t, and σ_t^c before January 1, 1996 (See Panel A of Table 1 for details). Between January 4, 1996 and December 31, 2019, there are 6,040 daily observations of spc_t and r_t^{spc} over 288 months.

For the time-series tests, we focus on the month-end value of r_t^{spc} to be consistent with the literature. However, we also report results based on daily data in Internet Appendix A. Panel A of Table 1 reports summary statistics that indicate an average value of r_t^{spc} around 10%, which suggests that it is a plausible measure of the discount rate. However, due to approximations, the variation of r_t^{spc} can be partially attributed to measurement errors. When we compare Equations (6) and (10), we observe that r_t^{spc} contains measurement error from ignoring the varying growth rate of dividend, i.e., $\bar{g} - g_{t,\tau}$. When the growth rate $g_{t,\tau}$ is temporarily high, r_t^{spc} underestimates the true discount rate r_t. As shown in Figure 1 and Figure A1, r_t^{spc} occasionally becomes negative when sampled at a high frequency, partly because the ignored dividend growth tends to pick up after a market crash.

It is important to note that a similar caveat applies to the common predictors like the dividend-price ratio (DP), which approximately measures $r_t - g_t$. A real-time measure for the discount rate based on DP generates negative predictions over one-third of the sample. To deal with the negative discount rate, Campbell and Thompson (2008) suggest truncating the value at zero. However, this

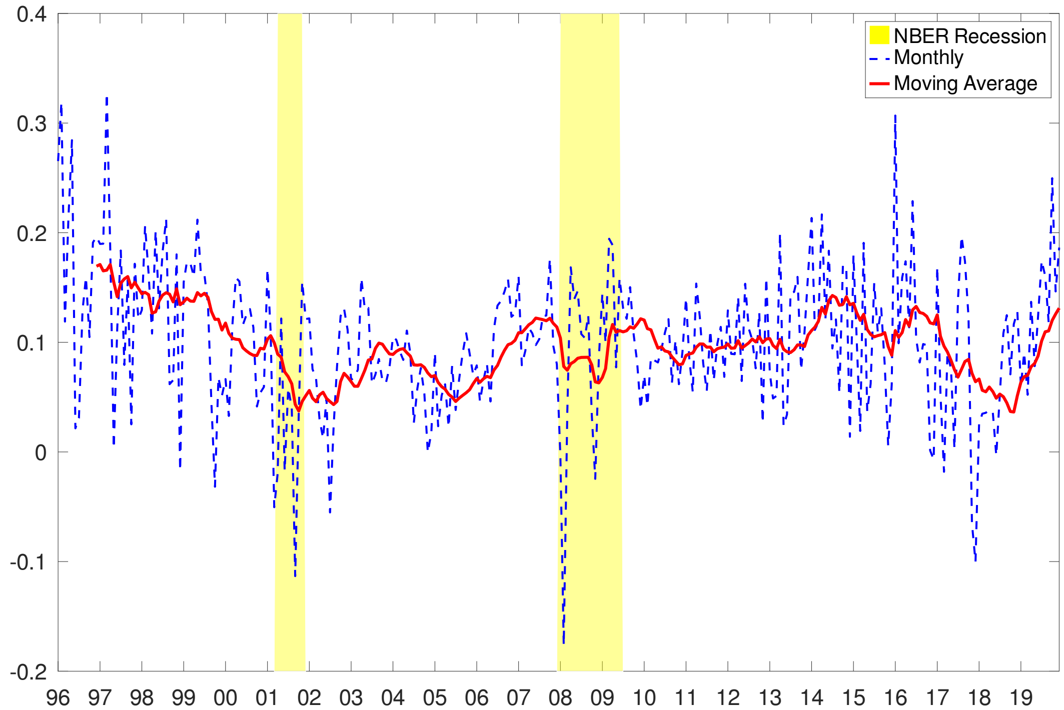

Figure 1: Time series of r_t^{spc}. The dashed line represents the monthly (month-end value) model-implied discount rate r_t^{spc} under constant parameters in Equation (10), with the solid line depicting the 12-month moving average. The shaded areas indicate NBER recessions. The date range is from January 1996 to December 2019.

is not necessary for r_t^{spc} as such incidence is relatively rare. Truncation slightly, but not significantly, improves the predictability of r_t^{spc}.

Our high frequency estimation results in the low persistence of r_t^{spc}. Panel A of Table 1 reveals a first-order autocorrelation of around 0.35. As a result, in the main cross-sectional tests, we treat the level of r_t^{spc} as an approximation of the shock. In Section 4.2.1, we conduct robustness tests using the innovation obtained from an AR(1) model, and the conclusions remain the same.

2.3 r_t^{spc} and Aggregate Stock Market Returns

Table 1 report our main result in the time series. We run the predictive regression of future 1-year market excess return $r_{t+h}^M - r_t^f$ (h=12) on model-implied premium $r_t^{spc} - r_t^f$

$$r_{t+h}^M - r_t^f = a + b \times (r_t^{spc} - r_t^f) + \varepsilon_t, \tag{11}$$

where r^M_{t+h} is calculated by compounding monthly market returns from months t to t + h, with data from Kenneth French's website (Rm-Rf + Rf).[4] The risk-free rate r^f_t is the 1-year rate at the end of month t from the linear interpolation of the zero-coupon yield curve provided in OptionMetrics. The regression is run at monthly frequency, and we adjust the t-statistics based on Newey and West (1987) with 12 lags. The results are presented in Panels B and C of Table 1.

For our main specification of r^{spc}_t with constant parameters, the coefficient on $r^{spc}_t - r^f_t$ is 0.786, which is significantly positive with a t-statistic of 4.63. The regression intercept is positive but indistinguishable from 0. In fact, the p-value for the equivalence test between $r^M_{t+1Y} - r^f_t$ and $r^{spc}_t - r^f_t$ is 0.341, indicating that we cannot reject their equivalence.

We also follow Welch and Goyal (2008) to calculate the out-of-sample R-squared as

$$R^2_{oos} = 1 - \frac{\sum_s [(r^{spc}_s - r^f_s) - (r^M_{s+1Y} - r^f_s)]^2}{\sum_s [his_s - (r^M_{s+1Y} - r^f_s)]^2}, \tag{12}$$

where his_s is the historical average of 1-year market excess return using all available data (starting at July 1926 from Kenneth French's website) until time s. The R^2_{oos} of r^{spc}_t under constant parameter version reaches 10.12%. To have a clearer view of the out-of-sample performance of r^{spc}_t over time, we plot the cumulative difference of the sum of squared errors (SSE) between the historical mean and model-implied forecast, i.e., $\sum_{s=Jan1996}^{t}\{[his_s - (r^M_{s+1Y} - r^f_s)]^2 - [(r^{spc}_s - r^f_s) - (r^M_{s+1Y} - r^f_s)]^2\}$. An increase of the cumulative SSE difference indicates a better forecast of return by r^{spc}_s relative to his_s at that point. From Figure 2, we can see that in general, the cumulative SSE difference increases over time.

The findings suggest that the model-implied discount rate r^{spc}_t is helpful in market timing compared to the historical average return. While the performance is arguably good, r^{spc}_t is created using a set of constant parameters, and we want to know if time-varying parameters can improve our predictions. In the subsequent analysis of Panel C, we construct r^{spc}_t with different choices of g_t, q_t, and σ^2_t. We obtain significant regression slopes that are close to 1 and insignificant intercepts. All p-values for equivalence test are larger than 10%. Furthermore, the out-of-sample R squares are all positive and comparable to the constant parameter version. Among the different combinations, we observe that time-varying volatility brings the most significant improvement.

[4] We use this definition of "market" to be consistent with the literature. The results with S&P 500 index are similar.

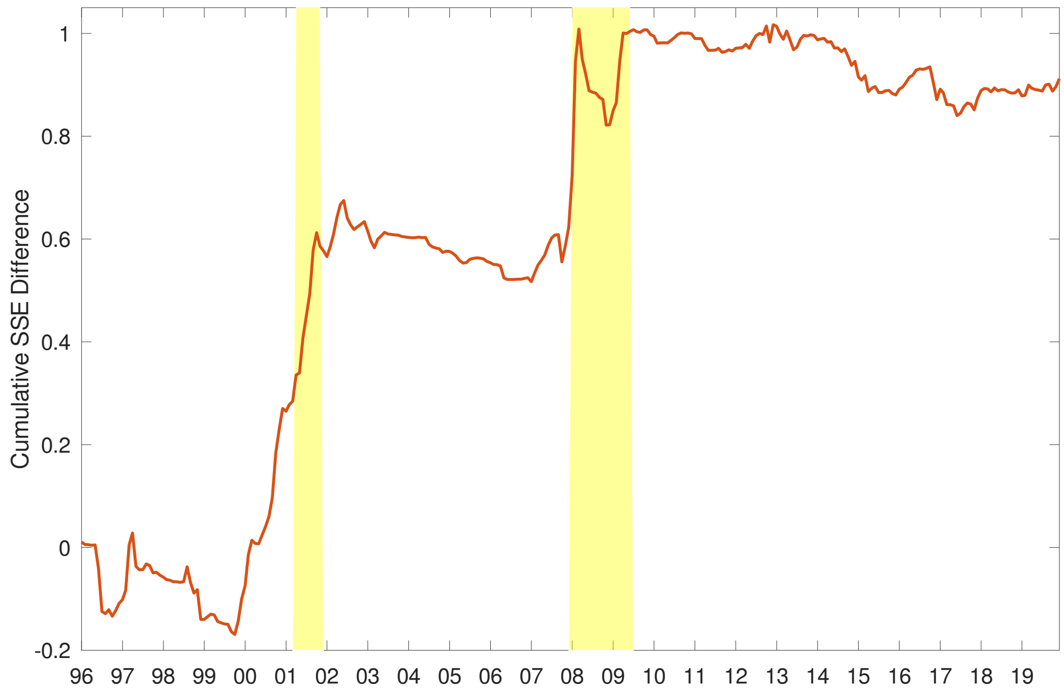

Figure 2: Cumulative Out-of-sample Out-Performance of Model-implied Forecast. This figure plots the cumulative difference of the sum of squared prediction errors (SSE) between the historical mean and the model-implied forecast (constant parameter version) for the future 1-year market excess return. The date range is from January 1996 to December 2019.

In Panel A of Table 2, we investigate whether the predictive ability of $r^{spc} - r^f$ is explained by other time-series predictors in the literature, which include the comprehensive list of predictors in Welch and Goyal (2008) from Amit Goyal's website,[5] the variance risk premium in Bollerslev, Tauchen and Zhou (2009) from Hao Zhou's website with the realized variance part from lag (VRP) or statistical forecast (EVRP), the lower bound of 1-year expected market excess return (RBnd) in Martin (2017), the cross-sectional average of call-put implied volatility spread from equity options (AIVS) in Han and Li (2021), the implied volatility difference between out-of-money put option and at-the-money call option for S&P 500 index option (VSk) in Atilgan, Bali and Demirtas (2015),

[5]The predictors in Welch and Goyal (2008) include the log of dividend-price ratio (DP), log of dividend-price (12-month lagged) ratio (DY), log of earnings-price ratio (EP), log of dividend-earning ratio (DE), the sum of squared daily returns on the S&P 500 (SVAR), the cross-sectional beta premium (CSP) in Polk, Thompson and Vuolteenaho (2006), the book-market ratio for the Dow Jones Industrial Average (BM), the net issues to market capitalization ratio (NTIS), the Treasury-bill rates (TBL), the long-term government bond yield (LTY), the long-term rate of returns (LTR), the term spread of Treasury bonds (TMS), the default yield spread, which is the difference between BAA and AAA-rated corporate bond yields, (DFY), the default return spread, which is the difference between long-term corporate bond and long-term government bond returns (DFR), the Consumer Price Index (INFL), the consumption, wealth, income ratio (CAY), and the investment-capital ratio (I/K).

and the implied volatility difference (or ratio minus 1) between at-the-money put and call options on the S&P 500 index (VSpd or VR) in Yan (2011).[6]

First, the coefficient on $r^{spc} - r^f$ is always significantly positive, regardless of the controlled predictors. Second, all the control predictors do not improve the predictive regression R-squares except for DY (1), EY (2), BM (7), and I/K (17). Among these four predictors, DP has the most significant improvement, reducing the coefficient of r^{spc} almost by 40%. This observation indicates that both the short and average[7] discount rates complement each other in shaping the market returns. Similarly, the significant improvement by the other three predictors are due to their various ties to the average discount rate.

Panel B of Table 2 examines the predictive ability of r_t^{spc} for future stock market return at different time horizons. Horizon h in Equation (11) can be 1, 3, 6, 12, or 24 months. The t-statistics are based on Newey and West (1987) with h lags. We can see that the coefficient on $r_t^{spc} - r_t^f$ is significantly positive for the 6-month to 2-year horizons. Moreover, we cannot reject the equivalence for all horizons at the 10% level.

In Internet Appendix A, we repeat the above time-series analysis using daily data and come to similar conclusions. Overall, the results suggest that the model-implied short-term dividend discount rate r_t^{spc} is a good proxy for the discount rate of the stock, which motivates us to investigate further through a cross-sectional study on the price of discount rate risk. We discuss the results in the following section.

3 r^{spc}-Beta and Cross-Sectional Stock Returns

In Section 2, we demonstrate that r^{spc}significantly predict market returns. We now explore how this discount rate risk is priced in the cross section of stocks. Given that r^{spc} can be estimated at daily frequency, it is straightforward to calculate individual stock's exposure to r^{spc}, which is named slope beta. We can thus infer the price of discount rate risk from the cross-sectional risk premium of the slope beta.

[6]AIVS, VSk, VSpd, and VR are constructed with the implied volatility data of Volatility Surface at 30-day maturity. The out-of-money (at-the-money) put is the put with delta -0.1 (-0.5), and the at-the-money call is the call with delta 0.5.

[7]The dividend-price ratio is the difference between the average discount and dividend growth rates.

3.1 r^{spc}-Beta

At the end of each month, for each stock, the slope beta on r^{spc}, β^{spc}, is estimated by regressing its daily excess return on the daily r^{spc} while controlling for the common factors:

$$r_s^i = \alpha_i + \beta_i^{spc} r_s^{spc} + \beta_i^{mkt}\mathrm{MKT}_s + \beta_i^{smb}\mathrm{SMB}_s + \beta_i^{hml}\mathrm{HML}_s + \beta_i^{umd}\mathrm{UMD}_s + \varepsilon_{i,s}, \tag{13}$$

where r_s^i is the excess return (over risk-free rate) of stock i at day s. Factors, MKT_s, SMB_s, HML_s, and UMD_s, are the contemporaneous daily factor returns of the Carhart (1997) four-factor model.

We run the regression for each stock at the end of each month, using its daily data over the past 12 months, and we require at least 200 valid observations. The daily stock return data is obtained from CRSP while the risk-free rate and factor returns are from Kenneth French's website. Since the daily r^{spc} starts from January 4, 1996, the resulting β^{spc} is available from the end of December 1996. In Internet Appendix A, we observe that the daily r^{spc} varies significantly over time and lacks persistence. As a result, we directly use the level of r^{spc} to represent shocks to discount rate in the main analysis for simplicity. However, we include the results using shocks from the AR(1) model in the robustness sections. In the robustness sections, we also include alternative factor returns as control.

3.2 Sample and Controls

We obtain the monthly stock return and characteristics from Chen and Zimmermann's (2022) open-source asset pricing dataset and restrict the sample to US common stocks listed on NYSE, NASDAQ, and AMEX. To mitigate the influence of micro-cap stocks, we focus on stocks with a market capitalization above the NYSE 20th size cutoff at the end of each month, where the NYSE size breakpoint data is from Kenneth French's website.[8]

To examine if β^{spc} contains distinct information for return prediction, we add a list of common stock risks or characteristics as controls, including the CAPM beta (β^{capm}), volatility beta (β^{vix}) in Ang, Hodrick, Xing and Zhang (2006), market capitalization (SIZE, in billions of dollars), book-to-market ratio (BM) in Fama and French (1992), momentum (MOM) in Jegadeesh and Titman (1993),

[8]In Internet Appendix C, we repeat the cross-sectional analysis for the all-stocks sample that does not restrict market capitalization and the large-cap sample that requires stocks to have a market capitalization above NYSE size 50th cutoff at the end of each month. The conclusions do not change.

reversal (REV) in Jegadeesh (1990), illiquidity (ILLIQ) in Amihud (2002), idiosyncratic volatility (IVOL) in Ang, Hodrick, Xing and Zhang (2006), total asset growth rate (AG) in Fama and French (2015), and the R&D-adjusted operating profitability (OPR) in Ball, Gerakos, Linnainmaa and Nikolaev (2015).[9] Most of these control variables are obtained from the open-source asset pricing dataset with minor modifications. Internet Appendix B provides detailed descriptions.

Our final sample contains monthly β^{spc} and other stock characteristics from December 1996 to December 2019 and the one-month-ahead stock return data from January 1997 to January 2020, resulting in 277 months of data. We only include stock-month observations with valid β^{spc} and one-month-ahead stock return, which results in 531,458 observations. Table 3 reports the summary statistics, with the time-series averages of cross-sectional statistics and correlation matrix in Panels A and B, respectively. For the main sample (above-NYSE-size-20th), we have about 1,919 stocks with valid β^{spc} each month on average, with an average cross-sectional mean of market capitalization around 8.6 billion dollars.

From Panel A of Table 3, we can see that the cross-sectional mean, median, and skewness of β^{spc} are all close to zero on average, which means that at each cross-section, approximately half of the stocks have positive β^{spc}. Panel B shows that β^{spc} has mild correlations with other stock characteristics, suggesting that β^{spc} captures distinct information.

3.3 Univariate Portfolio Analysis

As a first step of cross-sectional tests, we conduct univariate portfolio analysis to examine the relation between β^{spc} and one-month-ahead stock excess return. At the end of month t, the stocks are sorted into ten groups based on ascending order of β^{spc}. Table 4 reports the time-series averages of each portfolio's month t+1 excess returns (Raw) and the month t+1 high-minus-low returns (H-L) and alphas adjusted by factor models, which include CAPM, Fama-French (1992; 2015) three-factor and five-factor models (FF3 and FF5), Carhart (1997) four-factor model (FFC), Fama-French (2015) five-factor model plus momentum (FF6), and the Q5 model in Hou, Mo, Xue and Zhang (2021). We adjust the t-statistics based on Newey and West (1987) with six lags, which is approximately equal to $4 \times (T/100)^{2/9}$, as suggested by Bali, Engle and Murray (2016).

[9]Our results are robust to replacing OPR with the cash-based operating profitability in Ball, Gerakos, Linnainmaa and Nikolaev (2016).

In Table 4, we observe a positive relation between β^{spc} and one-month-ahead portfolio returns. With equal weighting, Panel A shows that the average portfolio excess return increases almost monotonically from 0.45% to 0.95% as β^{spc} increases, yielding a high-minus-low return of around 0.49% per month with a t-statistic of 2.81. This monthly return translates to an annualized return of around 5.88%, which is economically significant. Additionally, the alphas of high-minus-low return under different factor models are all statistically significant and close to the raw return. In Panel B, the value-weighted results exhibit high-minus-low return and alpha ranging from 0.63% to 0.72% per month (or 7.56% to 8.64% annually) and t-statistics almost all above 3. The positive predictive ability of β^{spc} is consistent with Merton's (1973) ICAPM that low-β^{spc} stocks, which negatively correlate with discount rate news, provide hedges against declines in investment opportunities and, therefore, earn low expected returns.

Table 5 reports the factor loadings of the high-minus-low returns on different factors. As shown, the loadings are never significantly positive but significantly negative on the momentum factor (the equal-weighted case) and value or investment factor (the value-weighted case), amplifying the magnitude of alphas. Moreover, the adjusted R-squares remain low across different factor models.

To examine if the predictive ability of β^{spc} for one-month-ahead stock return is stable over time, we plot in Figure 3 the cumulative sum of monthly high-minus-low return spread sorted by β^{spc}, with the equal-weighted (value-weighted) case on the left (right) panel. Both panels show upward trends, albeit more evident in the value-weighted case. Therefore, the predictive ability of β^{spc} is not restricted to specific periods.

Tables C1 and C4 in Internet Appendix C present the results of univariate portfolio analysis for the all-stocks sample and above-NYSE-size-50th sample. Unsurprisingly, the magnitude and t-statistics of the high-minus-low return and alphas are higher in the all-stocks sample and lower in the above-NYSE-size-50th sample. Nonetheless, they are all significantly positive. The result further confirms the predictive ability of β^{spc}.

3.4 Average Characteristics and Bivariate Portfolio Analysis

To examine whether the β^{spc}-sorting manifests the information of other stock characteristics, we first analyze the average characteristics of β^{spc}-sorted portfolios. At the end of month t, we calculate each stock characteristic's month-t equal-weighted average value across stocks within each β^{spc}-

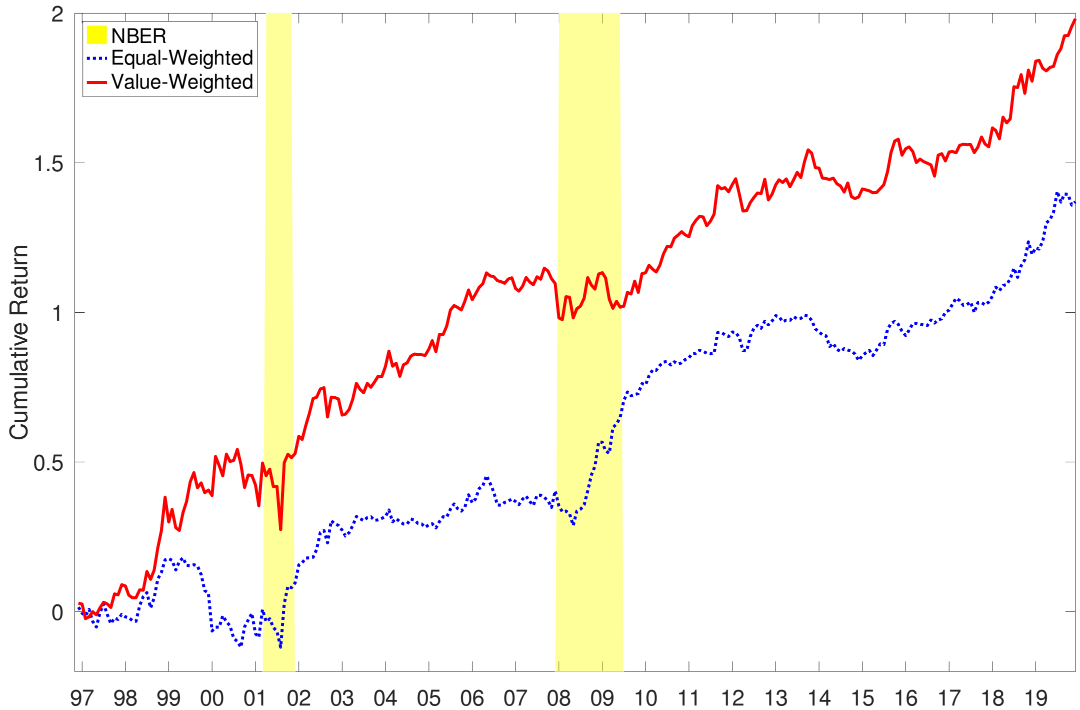

Figure 3: Cumulative β^{spc}-sorted Strategy Return. This figure plots the cumulative sum of β^{spc}-sorted High-minus-Low returns.

sorted portfolio. Table 6 reports the time-series averages of each portfolio's characteristics and the average difference between high-β^{spc} and low-β^{spc} groups.

We can see that, except β^{spc}, which increases monotonically by construction, only momentum and profitability exhibit significant differences between high-β^{spc} and low-β^{spc} groups. However, even for these two variables, the patterns are not monotonic.[10] This fact is consistent with Table 3, which shows that β^{spc} has very low correlations with other stock characteristics. The high-β^{spc} group tends to have higher profitability and experience higher returns in the past, compared with the low-β^{spc} group. Since momentum and profitability are positively related to future stock returns, they might explain the predictive ability of β^{spc}. However, as we will show later, this is not the case.

Next, we perform bivariate portfolio analysis to formally test if other stock characteristics can explain the predictive ability of β^{spc} for future stock return. At the end of month t, stocks are first

[10] Interestingly, the CAPM-β, momentum (MOM), reversal (REV), idiosyncratic volatility (IVOL), and asset growth (AG) exhibit a U-shaped pattern, and the market capitalization (SIZE) and R&D-adjusted operation profitability (OPR) exhibit an inverse U-shaped one.

sorted into ten groups based on one of the control variables. Then, within each control group, stocks are sorted into ten groups based on the ascending order of β^{spc}. The month t+1 equal-weighted and value-weighted excess returns for each of the 10×10 portfolios are calculated. Each β^{spc} group's month t+1 excess return is the average month t+1 excess return across ten groups sorted by the control variable.

Table 7 reports the time-series average of month t+1 excess return for each β^{spc} group and the high-minus-low portfolio after accounting for the effect of the control variables. For the high-minus-low portfolio, we only report its raw return and FF6 alpha for brevity. However, the alphas adjusted for other factor models are also significant. As shown, both the high-minus-low return spread and its six-factor alpha remain significantly positive regardless of the control variable or the weighting method.

Tables C2 and C5 in Internet Appendix C summarize the results of bivariate portfolio analysis for the all-stocks sample and above-NYSE-size-50th sample. The high-minus-low return and its six-factor alpha are significantly positive across different control variables and weighting methods in both samples. This result strengthens the finding that β^{spc} contains distinct information from other stock characteristics.

3.5 Fama-Macbeth Regressions

To simultaneously control for multiple predictors, we run the Fama-Macbeth (1973) regression of month t+1 stock excess return r^i_{t+1} on $\beta^{spc}_{i,t}$ and control variables at the end of month t. We winsorize all independent variables at the 0.5% and 99.5% levels monthly and adjust the t-statistics according to Newey and West (1987) with six lags. Table 8 presents the results.

In specification 1, where we do not add any control variables, the coefficient on β^{spc} is significantly positive, with a t-statistic of 3.15. As for the magnitude, a one-standard-deviation increase of β^{spc} leads to a 0.18% increase of next-month return (6.134%*0.03, where 0.03 is the average cross-sectional standard deviation of β^{spc} in Table 6), or 2.16% annually. In specification 2, we further control for the CAPM beta. The point estimate and significance level of the coefficient on β^{spc} are essentially unchanged; the coefficient on CAPM beta is slightly negative and insignificant. In specification 3, we further control for the volatility beta in Ang, Hodrick, Xing and Zhang (2006), which measures a stock's sensitivity to changes in expected volatility that is also related to changes in future investment opportunities. Again, the coefficient on β^{spc} remains almost unchanged, implying that β^{spc} also cannot explain the predictive ability of β^{spc}. The coefficient on β^{vix} is positive, inconsistent with Ang, Hodrick, Xing and Zhang (2006), but insignificant, which is due to the different stock samples and periods we use.

In specification 4, we control for the commonly used stock characteristics, including book-to-market ratio, size, momentum, reversal, illiquidity, idiosyncratic volatility, asset growth, and profitability. Although the magnitude of the coefficient on β^{spc} drops, it remains significant at the 1% level. This indicates that β^{spc} contains distinct information from these characteristics.[11]

Tables C3 and C6 in Internet Appendix C show that the coefficients on β^{spc} are significantly positive across all the regression specifications under both the all-stocks sample and above-NYSE-size-50th sample. Even for the above-NYSE-size-50th sample that mainly consists of large and liquid stocks, the positive coefficients on β^{spc} are significant at 1% level, which suggests the strong predictive ability of β^{spc}.

3.6 Longer Horizons

To investigate whether the predictive ability of β^{spc} extends beyond the one-month horizon, we conduct Fama-Macbeth regressions of the next h-months stock excess returns, denoted as r^i_{t+h}, on $\beta^{spc}_{i,t}$ at the end of month t. We employ four different regression specifications, as presented in Table 8. The excess returns r^i_{t+h} are calculated by compounding monthly stock returns from month t to month t+h and then subtracting the corresponding risk-free rate. We consider various horizons (h) of 3, 6, 9, and 12 months to assess the persistence of β^{spc}'s predictive power.

The results, presented in Table 9, reveal that the regression coefficients on β^{spc} are significantly positive across different specifications for the 3-month and 6-month horizons. This finding suggests that β^{spc} maintains its predictive ability for stock returns over these shorter time frames. However, when examining longer horizons of 9 and 12 months, we observe that while β^{spc} still exhibits some predictive power, the results are not consistently statistically significant across all specifications.

[11] As for the coefficients on characteristics, they are significantly negative for size, reversal, and asset growth and significantly positive for profitability, consistent with prior literature. The coefficients on book-to-market ratio, momentum, illiquidity, and idiosyncratic volatility are insignificant, and some even have wrong signs, which may result from the larger and more liquid sample we use and different periods from prior literature. The control variables generally have significant coefficients with correct signs for the all-stock sample in Table C3 of Internet Appendix C.

4 Robustness

4.1 Alternative Constructions of r^{spc}

4.1.1 Slope of Implied Volatility Spread

Equation (5) in Section 2.1 links the discount rate to the slope of the put-call implied volatility spread. However, in the main analysis, we use the implied volatility ratio, rather than the spread, to mitigate the volatility level effect. In this section, we use the spread and test its empirical performance in both time series and cross-section.

We define spc^{spread} as the regression slope of $\sigma_{t,\tau}^{(-0.5put)} - \sigma_{t,\tau}^{(0.5call)}$ on $\tau\sqrt{\tau}$, and calculate the corresponding discount rate as $r_t^{spread} = 3.18\% + 4.93\% - \frac{0.8}{4.93\%} spc_t$ with constant parameters as in Section 3. Table 10 reports the time-series predictive regression results for the alternative r^{spc}, focusing on the 1-year predictive horizon for brevity. As shown in the first row, $r^{spread} - r^f$ significantly and positively predicts future 1-year market excess returns. Moreover, the regression slope is close to 1 and the intercept is close to 0, resulting in a high p-value of approximately 0.988 for the equivalence test. Furthermore, the out-of-sample R-squared reaches 13.43%. These results suggest that our time-series findings are robust to r^{spread}. In fact, the results under r^{spread} are better than those with the original r^{spc} in Table 1.

For the cross-sectional results, the first row of Table 11 show that beta, β_{spread}^{spc}, based on r^{spread} still significantly and positively predicts one-month-ahead stock returns. However, the statistical significance is weaker than the original slope beta in Table 8. A possible reason is that r^{spread} is influenced by the volatility level, and therefore, β_{spread}^{spc} does not simply capture exposure to discount rate shocks.

4.1.2 At-the-money Option at Strike $K = Se^{(r^f - q)\tau}$

In the main analysis, we calculate *spc* as the slope of the implied volatility ratio of the put option with delta -0.5 over the call option with delta 0.5, which can be easily read from the Volatility Surface data. However, the strike prices at delta -0.5 and delta 0.5 are not precisely the at-the-money strikes in our theoretical model. For robustness, we construct alternative *spc* from at-the-money options with a strike price at $K = Se^{(r^f - q)\tau}$, where S is the stock price, r^f is the risk-free rate at corresponding maturities from linear interpolation of the zero-coupon yield curve in OptionMetrics, q is the index dividend yield from OptionMetrics, and τ is the maturity.

We first obtain the put and call implied volatilities at strike $K = Se^{(rf-q)\tau}$ through natural cubic spline interpolation of Volatility Surface (VS) data (implied volatility and implied strike at regular maturities) or option trading (TR) data in OptionMetrics (implied volatility and strike price at irregular maturities).[12] After obtaining the interpolated put and call implied volatilities, we calculate the put-call implied volatility ratio and the slope of it against $\tau\sqrt{\tau}$ as the new *spc*. Finally, the discount rate r^{spc} is obtained from the new *spc* with constant parameters as in Section 2.2. The two alternatives are denoted as r^{interp_VS} and r^{interp_TR}, respectively.

The time-series results in Table 10 indicate that the coefficients on both r^{interp_VS} and r^{interp_TR} remain significantly positive. However, the out-of-sample R-squared appears smaller than those in Table 1 and is negative for r^{interp_TR}. Relatedly, the equivalence between model-implied premium and future realized market excess return is also rejected under r^{interp_TR}. We suspect that this is due to the measurement errors of both the risk-free rate and the dividend yield when calculating the at-the-money strike, as well as the irregular maturities in option trading data for constructing r^{interp_TR}. In the cross-section, we estimate the alternative slope betas using r^{interp_VS} and r^{interp_TR} and denote them as $\beta^{spc}_{interp\_VS}$ and $\beta^{spc}_{interp\_TR}$, respectively. Panel A of Table 11 shows that both slope betas have significantly positive Fama-Macbeth (1973) regression coefficients across specifications, and the t-statistics are comparable to those in Table 8.

4.1.3 Maturity Selection

In the main analysis, we utilize all available maturities in Volatility Surface to construct *spc*. For robustness, we investigate whether excluding certain maturities would have a significant impact. We test two versions: the first excludes the 10-day maturity because it is unavailable before November 2005, and the second excludes maturities exceeding one year due to liquidity concerns. We denote the resulting two alternative r^{spc} as r^{ex10} and $r^{ex>1Y}$.

Regarding the cross-section, Panel A of Table 11 shows that the resulting slope betas β^{spc}_{ex10} and

[12] We filter the option trading data from OptionMetrics ("opprcd" file) as follows: (1) exclude records with missing implied volatility, time-to-maturity less than ten days, and non-positive best bid price; (2) if there are duplicate records with the same date, maturity, strike price, and option type, we keep the one with the largest volume or open interest.

$\beta^{spc}_{ex>1Y}$ have comparable performance to that of the original slope beta. For the time series, the last four rows of Table 10 show that r^{ex10} still has significant predictive ability, with results similar to those in Table 1. However, for $r^{ex>1Y}$, although the regression slope is significantly positive, it is far below one, resulting in the rejection of equivalence test. Furthermore, $r^{ex>1Y}$ performs poorly out-of-sample performance. The poor performance of $r^{ex>1Y}$ can be attributable to the estimation errors after excluding the longer maturities.

4.2 Alternative Slope Betas

4.2.1 Exposure to r^{spc} Innovations

In Section 3.1, we calculate slope beta as individual stock's exposure to the level of r^{spc}, as r^{spc} is not persistent. Here, for robustness, we use the AR(1) model to extract r^{spc} innovations and estimate slope beta as the stock's exposure to r^{spc} innovation. To make the estimation more accurate, we could use the full sample. However, this is not feasible for real-time investors. Therefore, we also consider two other options: using rolling past 12-month data, or using all available data until the end of the current month (with at least 12 months of data). We choose a 12-month window to match the estimation window of slope beta. After obtaining the r^{spc} innovations, we estimate the new slope beta using the same method as in Section 3.1, except replacing r^{spc} with r^{spc} innovations. These three alternative slope betas are denoted by $\beta^{spc}_{Full\_AR}$, $\beta^{spc}_{Roll\_AR}$, and $\beta^{spc}_{Expand\_AR}$, respectively.

Panel B of Table 11 shows that the alternative slope betas from r^{spc} innovations still positively and significantly predict future stock returns in Fama-Macbeth regression. However, the significance level is lower than the results of the original slope beta in Table 8. This may be due to the inaccurate estimation of r^{spc} innovations, as r^{spc} is not persistent.

4.2.2 Different Factor Controls

We estimate the slope beta via

$$r^i_s = a_i + \beta^{spc}_i r^{spc}_s + \sum_j \beta^j_i f_{j,s} + \varepsilon_{i,s}, \tag{14}$$

where $f_{j,s}$ represents the daily factor return of factor j at day s. In Equation (13), we choose $\{f_{j,s}\}$ to be the Carhart (1997) four factors in our main analyses. To determine if the results are sensitive to different factor controls, we examine five variants of $\{f_{j,s}\}$: market excess return only, Fama-French three factors, five factors, five factors plus momentum, or Q5 factors in Hou, Mo, Xue and Zhang (2021). The corresponding slope betas are denoted by β^{spc}_{MKT}, β^{spc}_{FF3}, β^{spc}_{FF5}, β^{spc}_{FF6}, and β^{spc}_{Q5}, respectively.

Panel C of Table 11 shows that the Fama-Macbeth regression coefficients on these alternative slope betas are all significantly positive across specifications, suggesting our findings are robust to alternative factor controls in the slope beta estimation.

4.3 Alternative Explanation

Our analysis is based on the no-arbitrage put-call parity that links the discount rate r^{spc} to *spc*, which we call the discount rate hypothesis. One can potentially come up with an alternative explanation based on the informed trading in the options market (Easley, O'Hara and Srinivas, 1998). For instance, insider information about a future market crash would result in the expensive pricing of long maturity put options and therefore a high *spc*. As a result, high *spc* predicts lower stock market return in the future. Stocks that positively co-vary with *spc* hedge against such crash and thus command lower expected returns. Since r^{spc} is a linear transformation of *spc*, this informed trading hypothesis explains the predictive ability of both r^{spc} in the time series and β^{spc} in the cross-section.

To distinguish between these two hypotheses, we turn to the individual stock options, where informed investors are more prevalent. If informed trading is the driving force, spc_i extracted from individual stock options should exhibit a strong negative predictive ability for cross-sectional stock returns. In contrast, individual stocks may subject to stringent short-sell constraints (Ofek, Richardson and Whitelaw, 2004) and the parameters of g_t, q_t, and σ^c_t in Equation (6) vary across stocks and over time. Thus, under our discount rate hypothesis, the predictive ability of *spc* does not necessarily extend to spc_i.

We use the same procedure as in Section 2.2 to calculate spc_i at the individual stock level. Hence, we only include stocks with valid options data and require valid pc^{τ}_t for at least ten maturities in Volatility Surface (11 maturities in total). We link the month-end spc_i to stocks using the CRSP-OptionMetrics linkage provided by WRDS. In the first four columns of Table 12, we run the Fama-Macbeth regression of month t+1 stock excess return on spc_i at the end of month t, with the same four sets of control variables as in Table 8. The coefficient on spc_i is significantly positive, contrary to the informed trading hypothesis. Since we now focus on stocks with options, we further control for the option-based predictors in column 5, including the implied volatility skew, IVSKEW (Xing, Zhang and Zhao, 2010), implied volatility spread, IVSPREAD (Yan, 2011), and risk-neutral skewness, RNS (Stilger and Poon, 2017).[13] After controlling for them, the coefficient on spc_i becomes insignificantly negative. In contrast, the coefficients on IVSKEW, IVSPREAD, and RNS are all significant, and the signs are consistent with the literature. This suggests that spc_i does not contain additional information.

In the following five columns, we include both spc_i and β^{spc}, with the same sets of controls as the first five columns. As before, the coefficient on spc_i changes from significantly positive to insignificantly negative when we include the option-based predictors. In comparison, the coefficient on β^{spc} remains significantly positive across different regression specifications, consistent with the findings in Section 3. Overall, the results do not support the informed trading hypothesis while lending further credence to our discount rate hypothesis.

5 Short-term Discount Rate and Investment Horizons

The empirical findings on β^{spc} are consistent with Merton's (1973) ICPAM, which suggests that investors may have different hedging demands based on how their consumption varies with the short-term discount rate. Intuitively, long-term investors may prefer to hedge away variations in short-term discount rates, and short-term investors may prefer to hold such risk for capturing short-term premiums. This implies that the effect of β^{spc} on the portfolio weight decreases with the investment horizon, being negative for long-term investors and potentially positive for short-term investors. In this section, we directly test this implication using the demand system approach of Koijen and Yogo (2019).

[13] We follow Yan (2011) to calculate IVSPREAD as the implied volatility difference between put (delta=-0.5) and call (delta=0.5) with 30-day maturity, and IVSKEW as the implied volatility difference between put (delta=-0.1) and call (delta=0.5) with 30-day maturity. Similarly, RNS is constructed using the 30-day maturity data from Volatility Surface, following the formulas in Bakshi, Kapadia and Madan (2003).

5.1 The Classification of Short-term and Long-term Institutions

Following the investment horizon literature, we adopt two common approaches to classify institutional investors into short-term or long-term types. The first approach directly uses the classification data from Brian Bushee, who categorizes institutions into three types: transient investors (TRA), dedicated investors (DED), and quasi-indexers (QIX). The underlying algorithm, developed by Bushee (1998) and modified in Bushee and Noe (2000) and Bushee (2001), is based on principal component and cluster analysis over a number of variables describing institutional portfolio turnover and diversification. According to Bushee (2001), TRA has high portfolio turnover and highly diversified holding, while DED (QIX) has low portfolio turnover and highly concentrated (diversified) holding. Following Giannetti and Yu (2021), we classify an institution as a short-term investor if its type is TRA, or a long-term investor if its type is either DED or QIX. For each institution, Bushee (2001) provides both varying types at the year level and permanent type through the mode of its varying types over the lifespan.

The second approach uses portfolio churn rate to determine the investment horizon, e.g., Gaspar, Massa and Matos (2005) and Yan and Zhang (2009). The intuition is that long-term investors trade less frequently than short-term investors. To this end, we first calculate the aggregate purchase and sale ($\mathrm{CR}_{\mathrm{buy},k,t}$ and $\mathrm{CR}_{\mathrm{sell},k,t}$) for institution k at quarter t as

$$\mathrm{CR}_{\mathrm{buy},k,t} = \sum_{i=1}^{N_k} \left| S_{k,i,t}P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\Delta P_{i,t} \right|, \qquad \text{for } S_{k,i,t} > S_{k,i,t-1} \tag{15}$$

$$\mathrm{CR}_{\mathrm{sell},k,t} = \sum_{i=1}^{N_k} \left| S_{k,i,t}P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\Delta P_{i,t} \right|, \qquad \text{for } S_{k,i,t} \leq S_{k,i,t-1}, \tag{16}$$

where N_k is the set of companies held by investor k, $P_{i,t-1}$ ($P_{i,t}$) is the share prices for stock i at the end of quarter t-1 (t), and $S_{k,i,t-1}$ ($S_{k,i,t}$) is the number of shares of stock i held by investor k at the end of quarter t-1 (t). The price and shares are adjusted by the CRSP price adjustment factor to account for stock splits and dividends.

We then compute two kinds of portfolio churn rate ($\mathrm{CR}^{\mathrm{Sum}}_{k,t}$ and $\mathrm{CR}^{\mathrm{Min}}_{k,t}$) for each institutional investor k at each quarter end t, following Gaspar, Massa and Matos (2005) and Yan and Zhang (2009), respectively.[14] The main difference is that Yan and Zhang (2009) use the minimum of

[14] We directly apply the SAS code provided by WRDS to obtain the aggregate purchase and sale ($\mathrm{CR}_{\mathrm{buy},k,t}$ and

aggregate purchase and sale to minimize the impact of investor cash flows on portfolio turnover.

$$\mathrm{CR}_{k,t}^{\mathrm{Sum}} = \frac{\mathrm{sum}(\mathrm{CR}_{\mathrm{buy},k,t}, \mathrm{CR}_{\mathrm{sell},k,t})}{\frac{1}{2}\sum_{i=1}^{N_k}(S_{k,i,t}P_{i,t} + S_{k,i,t-1}P_{i,t-1})}; \tag{17}$$

$$\mathrm{CR}_{k,t}^{\mathrm{Min}} = \frac{\mathrm{min}(\mathrm{CR}_{\mathrm{buy},k,t}, \mathrm{CR}_{\mathrm{sell},k,t})}{\frac{1}{2}\sum_{i=1}^{N_k}(S_{k,i,t}P_{i,t} + S_{k,i,t-1}P_{i,t-1})}. \tag{18}$$

Finally, at each quarter end, we divide institutions equally into three groups based on their average churn rate over the past 4 quarters, and label them as long-term (lowest churn rate group), mid-term, and short-term institutions (highest churn rate group) respectively.

In total, we have four types of investor horizon classifications, two based on Bushee's (2001) data (varying types or permanent type) and two based on the churn rate method ($\mathrm{CR}_{k,t}^{\mathrm{Sum}}$ and $\mathrm{CR}_{k,t}^{\mathrm{Min}}$). Compared with permanent type, Bushee's (2001) varying types at the year level have the advantage to capture the potential time-varying institutional behavior. However, they suffer from the missing value problem for young institutions without enough records. In addition, the varying types from year to year may result from measurement errors rather than the changing institutional nature. The churn rate method has the advantage of having classification available at quarterly frequency, and we can have finer classifications by dividing into more groups. However, it shares similar limitations with Bushee's (2001) varying types. Since none of these classifications is perfect, we present results based on each of them to demonstrate robustness.

5.2 A Demand System with β^{spc}

We use the demand system approach in Koijen and Yogo (2019, KY hereafter) and modify their code to incorporate slope beta. The demand system models the portfolio weight of stock i in investor j at time t, $\omega_{jt}(i)$, relative to her weight on outside asset $\omega_{jt}(0)$, as an exponentially affine function of stock characteristics:

$$\frac{\omega_{jt}(i)}{\omega_{jt}(0)} = \exp\left\{\theta_{jt} + \sum_{k=1}^{K}\theta_{k,jt}x_{kt}(i) + \theta_{\mathrm{slope},jt}\beta_{it}^{spc}\right\}\epsilon_{jt}(i) \tag{19}$$

where the slope beta β_{it}^{spc} is added as an additional characteristic to the original list of $\{x_{kt}(i)\}$, which includes market and book equities (both in logs), profitability, investment, dividend to book

$\mathrm{CR}_{\mathrm{sell},k,t}$), and churn rate $\mathrm{CR}_{k,t}^{\mathrm{Min}}$ ("TurnOver1" in the output), and modify the code to calculate $\mathrm{CR}_{k,t}^{\mathrm{Sum}}$.

equity, and market beta. The slope beta is winsorized at 2.5% and 97.5% levels on a monthly basis and its value at the end of month t-1 is matched with the institutional holdings at the end of quarter q (month t).[15] We also require the inside asset in KY, which is originally defined as common stocks with non-missing values of all six stock characteristics and returns, to have non-missing slope beta. The outside asset is simply the complementary set of stocks. We focus on the all-stocks sample as KY to increase the estimation accuracy of demand system and the cross-sectional variations of investors' investment horizons.

For our purpose, we change the institutional classification in KY to our classification by investment horizons according to the methods described in Section 5.1 and conduct the demand system estimation.[16] The household sector is the same as that in KY. For institutions with missing types of investment horizon, they are treated as a separate "unclassified" group. The demand system is estimated individually for each institution with more than 1,000 strictly positive holdings in the cross section of stocks. For institutions with fewer than 1,000 stock holdings, KY implement pooled estimation by bins according to institutional types (now under our types by investment horizons) and asset under management conditional on these types. Institutions belonging to the same bin have the same coefficients.

As suggested by KY, we focus on the nonlinear GMM estimation method. The estimated loadings on slope beta for different investors, $\theta_{slope,jt}$, start from 1997Q1 due to the availability of slope beta and end at 2017Q4 since we lack access to update some holding data provided by KY. At each quarter end, we calculate the asset-under-management-weighted (AUM-weighted) average of $\theta_{slope,jt}$ for investors within each type. The average time-series loading for each type of investor is summarized in Figure 4.

We find that, on average, long-term institutions have negative loadings on slope beta, while short-term institutions and household have positive loadings on average. The conclusions are robust to different classification methods of investor horizons. A negative loading on slope beta indicates that investor's portfolio weight on a stock increase as its slope beta decreases. Therefore, long-

[15] The winsorization at 2.5% and 97.5% levels on a monthly basis follows KY. As for the time matching, to make sure that the characteristics are available to investors when they make decisions, KY match the end of quarter q (month t)'s institutional holding data with the CAPM beta at the end of month t-1, and other accounting-related characteristics at the end of month t-6 by assuming a 6-month gap for accounting information release. Here, our choice about the timing of β^{spc} is same as that of CAPM beta.

[16] Originally, KY categorize institutions into 6 groups, including mutual fund, banks, investment advisors, insurance companies, pension funds, and others.

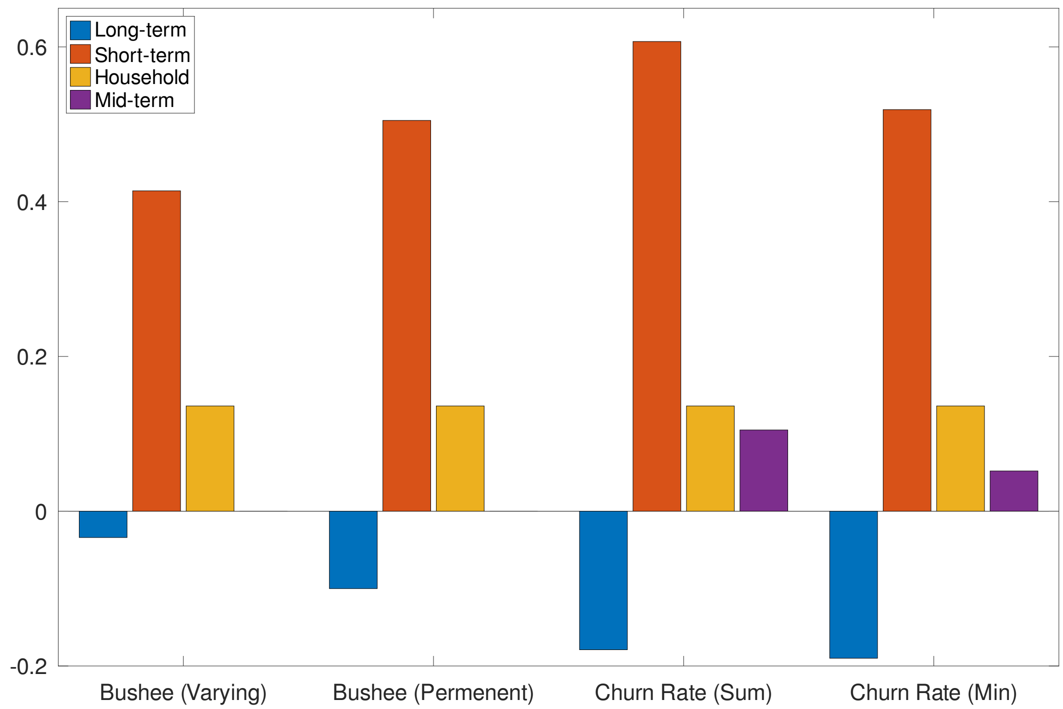

Figure 4: Average Loading on β^{spc} for Each Type of Investors. At each quarter end, we calculate the asset-under-management-weighted average of $\theta_{slope,jt}$ in Equation (19) for investors within each type. The figure plots the time-series average loading for each type of investors.

term institutions tilt their portfolios toward low slope beta stocks while short-term institutions and household do the opposite, consistent with Merton's (1973) ICAPM.

6 Conclusion

This paper introduces a new measure for the discount rate based on options data and investigates its implications in both time series and cross-section. We calculate the at-the-money put-call implied volatility ratio from S&P 500 index options and regress them on the corresponding maturities to obtain a slope measure (spc). We theoretically establish the relation between the short-term dividend discount rate and spc, and construct the model-implied discount rate measure r^{spc} accordingly. In the time series, r^{spc} performs well in both in-sample predictive regression and out-of-sample tests for future stock market return, indicating that r^{spc} closely approximates the discount rate of the aggregate stock.

In the cross-section, individual stocks' exposure to r^{spc} (slope beta, or β^{spc}) is positively associated with their future returns. High-β^{spc} stocks significantly outperform low-β^{spc} stocks by 0.49% (0.72%) per month under equal (value) weight. This result is robust to various controls and specifications. Our findings suggest that the price of discount rate risk is positive, consistent with Merton's (1973) ICAPM that investors hold low-β^{spc} stocks to hedge against declines in future investment opportunities.

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Table 1: Model-implied Discount Rate and Future Stock Market Returns

Panel A reports the summary statistics of the monthly (month-end value) model-implied discount rate r_t^{spc}, model-implied premium $r_t^{spc} - r_t^f$ under constant parameters in equation (10), and the corresponding future 1-year market excess return $r_{t+1Y}^M - r_t^f$. The "AR1" in the last column presents the first-order autocorrelation coefficient. Panel B summarizes the eight sets of parameter combinations $(2 \times 2 \times 2)$ used to calculate the model-implied discount rate. Panel C presents the in-sample predictive regression results and the out-of-sample R-squared (R^2_{oos}) under different parameter choices. The regression is conducted at a monthly frequency, with Newey and West (1987) adjusted t-stats (12 lags) reported in parentheses. We also report the p-value of the Wald test for the equivalence between model-implied premium and future market excess return. The sample covers the period from January 1996 to December 2019.

Panel A: Summary statistics

	Obs.	Mean	Std.	Min	P25	P50	P75	Max	Skew	AR1
r_t^{spc} (%)	288	10.04	6.69	-17.64	6.17	10.22	14.08	32.72	-0.08	0.35
$r_t^{spc} - r_t^f$ (%)	288	7.21	6.81	-20.09	3.21	7.28	11.50	30.00	-0.19	0.38
$r_{t+1Y}^M - r_t^f$ (%)	288	7.55	17.56	-45.08	0.01	10.76	18.48	53.90	-0.75	0.92

Panel B: Choices of g, q, and σ in $r_t^{spc} = g + q - \frac{2N'(0)\sigma}{q} spc_t$

$\bar{g}$	3.18%	The mean dividend growth rate of S&P 500 index between January 1871 and December 1995, where the dividend growth rate is the log ratio of past 12-month dividend to its lagged 12-month value, using data from Amit Goyal's website (starts at Jan 1871).
g_t	time-varying	The mean dividend growth rate of S&P 500 index from January 1871 to time t.
$\bar{q}$	4.93%	The mean dividend yield of S&P 500 index between January 1871 and December 1995, where the dividend yield is the past 12-month dividend divided by the lagged 12-month price, using data from Amit Goyal's website (starts at Jan 1871)
q_t	time-varying	The mean dividend yield of S&P 500 index from January 1871 to time t.
$\bar{\sigma}$	20.47%	The standard deviation of the annual S&P 500 returns from 1926 to 1995. Note that the S&P 500 return data in CRSP is available from 1926, while the implied volatility data is not available prior to 1996.
σ_t^c	time-varying	The at-the-money call implied volatility with 1-year maturity at time t for the S&P 500 index option in Volatility Surface of OptionMetrics.

Panel C: Results of predictive regression: $r_{t+1Y}^M - r_t^f = a + b \times (r_t^{spc} - r_t^f) + \varepsilon_t$

Specification	a	b	Adj. R^2	$p(a=0, b=1)$	R^2_{oos}
$\bar{g}$, $\bar{q}$, $\bar{\sigma}$ (main specification)	0.019	0.786***	9.00%	0.341	10.12%
	(0.52)	(4.63)			
$\bar{g}$, $\bar{q}$, σ_t^c	0.013	0.876***	10.03%	0.729	11.53%
	(0.38)	(5.24)			
g_t, $\bar{q}$, $\bar{\sigma}$	0.018	0.783***	8.98%	0.317	10.04%
	(0.49)	(4.59)			
g_t, $\bar{q}$, σ_t^c	0.012	0.872***	10.02%	0.702	11.48%
	(0.35)	(5.18)			
$\bar{g}$, q_t, $\bar{\sigma}$	0.024	0.733***	8.57%	0.151	9.26%
	(0.68)	(4.64)			
$\bar{g}$, q_t, σ_t^c	0.019	0.824***	9.65%	0.470	10.93%
	(0.54)	(5.31)			
g_t, q_t, $\bar{\sigma}$	0.023	0.731***	8.56%	0.139	9.21%
	(0.65)	(4.60)			
g_t, q_t, σ_t^c	0.018	0.821***	9.64%	0.447	10.90%
	(0.51)	(5.25)			

Table 2: Predictive Regression with Controls and Different Horizons

Panel A presents the regression results of $r^M_{t+1Y} - r^f_t$ on $r^{spc}_t - r^f_t$, with other time-series predictors as control one by one. Panel B shows the regression of future stock market excess return at different horizons $r^M_{t+h} - r^f_t$ on $r^{spc}_t - r^f_t$, where $r^M_{t+h} - r^f_t$ is the annualized h-months market excess returns from month t+1 to month t+h (both inclusive), where the horizon h can be 1, 3, 6, 12, or 24 months. In both panels, the regression is run at monthly frequency and the t-statistics in parentheses are adjusted for autocorrelation using Newey and West (1987) standard errors with lags equal to the overlapping length. The month t ranges from January 1996 to December 2019.

Panel A: $r^M_{t+1Y} - r^f_t = a + b \times (r^{spc}_t - r^f_t) + c \times control_t + \varepsilon_t$ with different controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
control	DP	DY	EP	DE	SVAR	CSP	BM	NTIS	TBL	LTY	LTR	TMS
a	1.60	1.41	0.09	0.08	0.01	-0.05	-0.21	0.02	0.07	0.11	0.02	-0.03
	(3.26)	(3.60)	(0.36)	(1.73)	(0.17)	(-0.59)	(-2.09)	(0.56)	(2.16)	(1.56)	(0.49)	(-0.53)
b	**0.48**	**0.42**	**0.79**	**0.74**	**0.81**	**0.95**	**0.60**	**0.78**	**0.66**	**0.70**	**0.79**	**0.74**
	(2.51)	(2.19)	(4.60)	(4.33)	(4.62)	(4.84)	(4.25)	(4.34)	(4.49)	(4.71)	(4.59)	(4.65)
c	0.39	0.35	0.02	0.07	3.57	-24.88	0.92	1.76	-2.05	-1.95	0.17	2.32
	(3.26)	(3.51)	(0.28)	(1.85)	(1.70)	(-0.66)	(2.80)	(1.11)	(-1.54)	(-1.10)	(0.60)	(1.44)
Adj.R^2	27.4%	25.3%	8.9%	11.3%	9.7%	11.8%	21.7%	12.3%	14.1%	11.3%	8.8%	11.7%
N	288	288	288	288	288	84	288	288	288	288	288	288

	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
control	DFY	DFR	INFL	CAY	I/K	VRP	EVRP	RBnd	AIVS	VSk	VSpd	VR
a	-0.04	0.02	0.03	0.01	0.65	0.00	0.01	-0.04	0.03	-0.06	0.01	0.01
	(-0.74)	(0.54)	(1.05)	(0.26)	(2.20)	(0.11)	(0.16)	(-0.87)	(0.80)	(-0.90)	(0.34)	(0.20)
b	**0.76**	**0.78**	**0.79**	**1.03**	**0.79**	**0.77**	**0.80**	**0.78**	**0.79**	**0.69**	**0.90**	**0.98**
	(4.61)	(4.70)	(4.55)	(4.63)	(3.72)	(4.47)	(4.61)	(4.45)	(4.84)	(4.14)	(4.19)	(4.07)
c	6.29	0.54	-8.73	0.17	-17.34	0.10	0.07	1.54	1.29	1.01	-1.38	-0.35
	(1.45)	(0.90)	(-2.22)	(0.18)	(-2.03)	(1.80)	(1.58)	(1.97)	(1.97)	(1.90)	(-1.10)	(-1.34)
Adj.R^2	10.9%	9.0%	11.7%	12.9%	22.6%	10.3%	9.5%	12.0%	10.0%	11.2%	9.6%	10.3%
N	288	288	288	96	96	288	288	288	288	288	288	288

Panel B: $r^M_{t+h} - r^f_t = a + b \times (r^{spc}_t - r^f_t) + \varepsilon_t$ with different horizon h

	(1)	(2)	(3)	(4)	(5)
h	$1M$	$2M$	$6M$	$1Y$	$2Y$
a	0.051	0.032	0.033	0.019	0.034
	(1.18)	(0.88)	(1.08)	(0.52)	(0.91)
b	0.313	0.519*	0.524**	0.786***	0.661***
	(0.80)	(1.75)	(2.33)	(4.63)	(3.75)
Adj.R^2	-0.19%	0.87%	2.04%	9.00%	9.33%
$p(a=0, b=1)$	0.217	0.265	0.107	0.341	0.131
N	288	288	288	288	288

Table 3: Summary Statistics of Cross-sectional Variables

This table shows the summary statistics for the cross-sectional predictors, including slope beta (β^{spc}), CAPM beta (β^{capm}), volatility beta (β^{vix}), book-to-market ratio (BM), market capitalization in billions of dollars (SIZE), momentum (MOM), reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), asset growth (AG), and profitability (OPR). Panel A presents the time-series averages of the cross-sectional statistics (the "N" column is the time-series average of cross-sectional stock number). Panel B shows the time-series average of the cross-sectional correlation matrix, with the lower (upper) triangle referring to the Pearson (Spearman) correlation coefficient. The data ranges from December 1996 to December 2019, including only those common stocks with valid β^{spc} and next month return and above the NYSE size 20th cutoff at the end of each month.

Panel A: Average cross-sectional statistics

	Mean	Std.	Min	5%	25%	50%	75%	95%	Max	Skew	N
β^{spc}	0.000	0.030	-0.203	-0.045	-0.015	0.000	0.016	0.047	0.198	-0.100	1,919
β^{capm}	1.081	0.465	-0.204	0.446	0.757	1.010	1.337	1.957	3.247	0.747	1,919
β^{vix}	0.001	0.009	-0.065	-0.012	-0.004	0.000	0.005	0.014	0.071	0.154	1,919
BM	0.543	0.443	0.003	0.105	0.268	0.451	0.709	1.234	6.739	3.861	1,738
SIZE	8.568	26.826	0.497	0.563	0.950	1.967	5.421	33.152	481.753	8.974	1,919
MOM	0.211	0.571	-0.784	-0.349	-0.069	0.117	0.350	1.037	9.247	5.060	1,906
REV	0.018	0.119	-0.473	-0.143	-0.043	0.011	0.069	0.197	1.398	2.097	1,919
ILLIQ	0.020	0.282	0.000	0.000	0.001	0.003	0.009	0.051	10.862	27.299	1,906
IVOL	0.018	0.012	0.001	0.007	0.011	0.015	0.022	0.038	0.183	4.448	1,919
AG	0.202	0.738	-0.745	-0.130	0.005	0.081	0.209	0.834	19.567	13.606	1,785
OPR	0.171	0.123	-0.964	0.018	0.111	0.162	0.225	0.358	0.969	-0.587	1,360

Panel B: Average cross-sectional correlation

	β^{spc}	β^{capm}	β^{vix}	BM	SIZE	MOM	REV	ILLIQ	IVOL	AG	OPR
β^{spc}		0.018	0.003	-0.001	0.007	0.045	0.020	0.008	-0.010	0.013	0.021
β^{capm}	0.021		0.057	-0.099	-0.115	-0.014	-0.006	0.056	0.431	0.086	-0.109
β^{vix}	0.002	0.055		-0.001	-0.049	-0.031	0.000	0.041	0.048	0.012	-0.011
BM	0.001	-0.056	-0.006		-0.165	-0.002	0.006	0.198	-0.123	-0.202	-0.471
SIZE	-0.002	-0.062	-0.027	-0.079		0.062	0.017	-0.891	-0.325	-0.013	0.172
MOM	0.038	0.043	-0.024	0.006	-0.005		-0.001	0.083	-0.034	-0.032	0.003
REV	0.019	0.004	0.001	0.009	-0.004	0.011		0.056	0.035	-0.006	-0.001
ILLIQ	-0.005	-0.057	0.000	0.076	-0.037	0.069	0.038		0.232	-0.020	-0.203
IVOL	-0.008	0.375	0.042	-0.049	-0.138	0.064	0.167	0.051		0.104	-0.120
AG	0.005	0.092	0.010	-0.055	-0.012	-0.010	-0.008	0.004	0.096		0.107
OPR	0.020	-0.120	-0.009	-0.329	0.106	-0.064	-0.022	-0.077	-0.129	-0.049	

Table 4: Portfolio Returns Sorted by β^{spc}

This table presents the results of a univariate portfolio analysis. At the end of month t, stocks are sorted into ten groups based on the ascending order of β^{spc}. The table reports the time-series averages of each portfolio's month t+1 excess returns (Raw) and the month t+1 high-minus-low returns (H-L), as well as their alphas adjusted for different factor models, including the CAPM, Fama-French three-factor and five-factor models (FF3 and FF5), Carhart four-factor model (FFC), Fama-French five-factor model plus momentum (FF6), and the Q5 model in Hou, Mo, Xue and Zhang (2021). The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The month-end t ranges from December 1996 to December 2019, and the sample includes only those common stocks above the NYSE size 20th cutoff at the end of each month.

Panel A: Equal-weighted return and α (%)											
	Low	2	3	4	5	6	7	8	9	High	H-L
Raw	0.45	0.69	0.69	0.78	0.76	0.79	0.86	0.88	0.90	0.95	0.49***
	(1.01)	(2.05)	(2.23)	(2.65)	(2.63)	(2.85)	(3.08)	(2.82)	(2.65)	(2.28)	(2.81)
CAPM	-0.47	-0.06	0.01	0.13	0.13	0.17	0.23	0.19	0.15	0.01	0.49***
	(-2.24)	(-0.48)	(0.10)	(0.88)	(0.79)	(1.24)	(1.69)	(1.25)	(1.05)	(0.07)	(2.66)
FF3	-0.47	-0.08	-0.03	0.09	0.07	0.12	0.18	0.14	0.12	0.03	0.50***
	(-3.63)	(-1.10)	(-0.45)	(1.13)	(0.87)	(1.36)	(2.70)	(1.59)	(1.39)	(0.21)	(2.64)
FFC	-0.41	-0.05	0.02	0.11	0.12	0.17	0.21	0.20	0.18	0.19	0.59***
	(-3.36)	(-0.68)	(0.38)	(1.48)	(1.40)	(2.03)	(2.98)	(2.39)	(2.27)	(1.80)	(3.36)
FF5	-0.25	-0.10	-0.07	0.01	-0.05	0.03	0.09	0.06	0.12	0.26	0.51**
	(-2.13)	(-1.25)	(-1.10)	(0.19)	(-0.69)	(0.34)	(1.58)	(0.87)	(1.38)	(1.83)	(2.51)
FF6	-0.21	-0.07	-0.03	0.04	-0.01	0.07	0.12	0.11	0.17	0.37	0.58***
	(-1.86)	(-0.93)	(-0.52)	(0.51)	(-0.21)	(0.96)	(1.95)	(1.70)	(2.15)	(3.14)	(3.17)
Q5	-0.08	0.05	0.02	0.08	0.02	0.11	0.14	0.10	0.21	0.47	0.55***
	(-0.69)	(0.69)	(0.22)	(0.89)	(0.15)	(1.11)	(1.89)	(1.13)	(2.21)	(3.07)	(2.61)

Panel B: Value-weighted return and α (%)											
	Low	2	3	4	5	6	7	8	9	High	H-L
Raw	0.30	0.62	0.62	0.57	0.63	0.57	0.62	0.74	0.79	1.02	0.72***
	(0.70)	(1.97)	(2.10)	(2.04)	(2.35)	(2.14)	(2.36)	(2.83)	(2.23)	(2.37)	(3.94)
CAPM	-0.51	-0.03	0.02	-0.03	0.07	-0.01	0.06	0.11	0.08	0.12	0.63***
	(-3.05)	(-0.34)	(0.22)	(-0.34)	(0.74)	(-0.11)	(0.69)	(1.06)	(0.56)	(0.68)	(3.13)
FF3	-0.51	-0.04	0.01	-0.03	0.05	-0.02	0.04	0.10	0.10	0.16	0.66***
	(-3.12)	(-0.42)	(0.11)	(-0.38)	(0.65)	(-0.27)	(0.55)	(1.05)	(0.77)	(1.17)	(3.47)
FFC	-0.41	-0.05	-0.01	-0.05	0.01	-0.00	0.04	0.14	0.16	0.27	0.68***
	(-2.58)	(-0.44)	(-0.09)	(-0.51)	(0.19)	(-0.06)	(0.45)	(1.46)	(1.30)	(1.96)	(3.38)
FF5	-0.27	-0.10	-0.05	-0.08	-0.03	-0.03	-0.08	0.12	0.18	0.39	0.66***
	(-1.95)	(-0.85)	(-0.55)	(-0.86)	(-0.44)	(-0.38)	(-1.03)	(1.34)	(1.30)	(2.70)	(3.21)
FF6	-0.21	-0.10	-0.06	-0.09	-0.05	-0.02	-0.08	0.15	0.22	0.46	0.67***
	(-1.49)	(-0.85)	(-0.65)	(-0.90)	(-0.73)	(-0.21)	(-1.00)	(1.66)	(1.65)	(3.32)	(3.18)
Q5	-0.16	-0.08	-0.04	-0.12	-0.12	-0.02	-0.06	0.12	0.20	0.47	0.63***
	(-1.04)	(-0.69)	(-0.42)	(-1.17)	(-1.61)	(-0.27)	(-0.69)	(1.19)	(1.48)	(3.18)	(2.89)

Table 5: Factor Loadings of β^{spc}-sorted High-minus-Low Return Spread

This table presents the regression results of the β^{spc}-sorted high-minus-low return spread on common factors, with the equal-weighted (value-weighted) case in Panel A (Panel B). The factor models include CAPM, Fama-French three-factor and five-factor models (FF3 and FF5), Carhart four-factor model (FFC), Fama-French five-factor model plus momentum (FF6), and the Q5 model in Hou, Mo, Xue and Zhang (2021). Both the return spread and factor returns are in percentage. The t-statistics in parentheses are adjusted according to Newey and West (1987), with six lags.

Panel A: Equal-weighted return spread

	CAPM	FF3	FFC	FF5	FF6		Q5
Alpha	0.49***	0.50***	0.59***	0.51**	0.58***	Alpha	0.55***
	(2.66)	(2.64)	(3.36)	(2.51)	(3.17)		(2.61)
MKT	0.01	0.03	-0.03	0.02	-0.03	MKT	0.01
	(0.14)	(0.49)	(-0.60)	(0.39)	(-0.47)		(0.15)
SMB		-0.13	-0.11	-0.11	-0.08	ME	-0.15
		(-1.32)	(-1.30)	(-1.36)	(-0.98)		(-1.49)
HML		-0.06	-0.12	-0.00	-0.09	I/A	-0.10
		(-0.63)	(-1.34)	(-0.03)	(-0.87)		(-0.79)
RMW				0.06	0.09	ROE	-0.04
				(0.43)	(0.79)		(-0.35)
CMA				-0.13	-0.09	EG	0.01
				(-0.98)	(-0.79)		(0.05)
UMD			-0.14**		-0.14**		
			(-2.47)		(-2.47)		
Adj. R^2	-0.35%	1.11%	6.53%	1.15%	6.68%	Adj. R^2	1.61%
N	277	277	277	277	277	N	277

Panel B: Value-weighted return spread

	CAPM	FF3	FFC	FF5	FF6		Q5
Alpha	0.63***	0.66***	0.68***	0.66***	0.67***	Alpha	0.63***
	(3.13)	(3.47)	(3.38)	(3.21)	(3.18)		(2.89)
MKT	0.13	0.11	0.10	0.11	0.10	MKT	0.12
	(1.41)	(1.30)	(1.32)	(1.22)	(1.22)		(1.42)
SMB		0.02	0.02	0.05	0.06	ME	0.02
		(0.16)	(0.18)	(0.44)	(0.44)		(0.22)
HML		-0.23**	-0.24**	-0.20*	-0.21	I/A	-0.28*
		(-2.12)	(-2.04)	(-1.68)	(-1.63)		(-1.86)
RMW				0.10	0.10	ROE	0.09
				(0.66)	(0.67)		(0.52)
CMA				-0.17	-0.16	EG	0.03
				(-0.95)	(-0.96)		(0.14)
UMD			-0.02		-0.02		
			(-0.19)		(-0.18)		
Adj. R^2	1.83%	4.66%	4.35%	4.68%	4.37%	Adj. R^2	2.63%
N	277	277	277	277	277	N	277

Table 6: Average Characteristics of β^{spc}-sorted Portfolios

This table presents the average characteristics of portfolios sorted by β^{spc}. At the end of month t, stocks are sorted into ten groups in ascending order of β^{spc}. The table displays the time-series averages of each portfolio's characteristics and the average characteristic differences between the high-β^{spc} and low-β^{spc} portfolios (H-L). The t-statistics for the H-L differences in the last column are adjusted according to Newey and West (1987) with six lags. The sample period spans from December 1996 to December 2019, and the sample includes only common stocks above the NYSE size 20th cutoff at the end of each month.

	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)
β^{spc}	-0.052	-0.025	-0.015	-0.008	-0.003	0.003	0.009	0.016	0.026	0.054	0.106***	(18.08)
β^{capm}	1.261	1.090	1.026	0.991	0.987	0.988	1.005	1.046	1.113	1.303	0.042	(1.59)
β^{vix}	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.000	(0.72)
BM	0.543	0.535	0.543	0.544	0.544	0.548	0.547	0.547	0.537	0.544	0.001	(0.06)
SIZE	4.296	7.286	9.323	11.158	11.701	11.202	10.349	8.801	7.099	4.438	0.142	(0.54)
MOM	0.269	0.198	0.185	0.172	0.173	0.175	0.180	0.190	0.219	0.354	0.085**	(2.20)
REV	0.023	0.015	0.015	0.014	0.015	0.015	0.015	0.017	0.018	0.032	0.008	(1.24)
ILLIQ	0.026	0.020	0.021	0.018	0.020	0.020	0.018	0.017	0.016	0.024	-0.001	(-0.23)
IVOL	0.025	0.019	0.017	0.016	0.015	0.015	0.016	0.017	0.019	0.025	-0.000	(-0.62)
AG	0.281	0.201	0.180	0.168	0.161	0.162	0.174	0.185	0.206	0.298	0.017	(0.67)
OPR	0.150	0.169	0.172	0.175	0.177	0.178	0.177	0.176	0.173	0.158	0.008*	(1.93)

Table 7: Portfolio Returns Sorted by β^{spc}: Control for Other Variables

This table presents the results of a bivariate portfolio analysis. The analysis is conducted as follows: at the end of month t, stocks are sorted into ten groups based on each control variable separately. Within each control group, stocks are further sorted into ten subgroups in ascending order of β^{spc}. For each of the resulting 10×10 portfolios, equal-weighted and value-weighted excess returns are calculated for the following month, t+1. The table reports the average month t+1 return for each β^{spc} group, which is computed as the average return across the ten subgroups sorted by the control variable. These time-series averages are expressed in percentage terms. Additionally, the table includes the high-minus-low return (H-L), its alpha (FF6 α) adjusted for the Fama-French five-factor plus momentum model, and their corresponding t-statistics in parentheses. The t-statistics are adjusted using the method proposed by Newey and West (1987), with six lags. The analysis covers the period from December 1996 to December 2019, and the sample is restricted to common stocks above the NYSE size 20th cutoff at the end of each month.

Panel A: Equal-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	FF6 α
β^{capm}	0.50	0.68	0.70	0.72	0.73	0.81	0.89	0.84	0.87	0.99	0.49***(*2.90*)	0.49***(*2.94*)
β^{vix}	0.45	0.73	0.72	0.75	0.77	0.77	0.84	0.87	0.85	1.00	0.55***(*3.54*)	0.59***(*3.65*)
BM	0.57	0.73	0.74	0.76	0.79	0.84	0.87	0.87	0.94	0.99	0.42***(*2.77*)	0.52***(*3.15*)
SIZE	0.43	0.68	0.71	0.76	0.78	0.80	0.88	0.91	0.81	0.97	0.54***(*3.02*)	0.63***(*3.43*)
MOM	0.48	0.68	0.76	0.74	0.80	0.82	0.88	0.90	0.89	0.85	0.37** (*2.57*)	0.43***(*2.72*)
REV	0.51	0.68	0.70	0.72	0.81	0.83	0.82	0.83	0.84	1.02	0.51***(*3.54*)	0.57***(*3.68*)
ILLIQ	0.43	0.74	0.70	0.71	0.80	0.86	0.84	0.90	0.82	1.00	0.56***(*3.49*)	0.64***(*3.71*)
IVOL	0.51	0.77	0.64	0.74	0.85	0.75	0.80	0.86	0.84	0.99	0.48***(*3.48*)	0.54***(*3.69*)
AG	0.56	0.72	0.75	0.79	0.76	0.80	0.87	0.90	0.88	1.05	0.49***(*3.01*)	0.58***(*3.45*)
OPR	0.45	0.72	0.66	0.73	0.82	0.77	0.87	0.89	0.90	1.00	0.55***(*3.30*)	0.67***(*3.47*)

Panel B: Value-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	FF6 α
β^{capm}	0.34	0.62	0.63	0.59	0.67	0.63	0.73	0.76	0.65	0.99	0.65***(*3.79*)	0.62***(*3.23*)
β^{vix}	0.30	0.63	0.68	0.62	0.68	0.52	0.76	0.64	0.80	0.93	0.63***(*3.95*)	0.62***(*3.42*)
BM	0.47	0.68	0.66	0.60	0.70	0.66	0.66	0.77	0.89	0.96	0.48***(*2.78*)	0.51***(*2.61*)
SIZE	0.43	0.67	0.71	0.75	0.78	0.80	0.88	0.91	0.81	0.96	0.54***(*2.98*)	0.62***(*3.34*)
MOM	0.30	0.63	0.62	0.59	0.72	0.63	0.68	0.90	0.77	0.79	0.49***(*3.12*)	0.53***(*2.76*)
REV	0.42	0.63	0.66	0.61	0.63	0.62	0.65	0.78	0.79	1.00	0.58***(*3.71*)	0.63***(*3.34*)
ILLIQ	0.45	0.67	0.70	0.66	0.79	0.81	0.80	0.89	0.82	1.00	0.54***(*3.14*)	0.55***(*2.96*)
IVOL	0.32	0.68	0.54	0.63	0.61	0.63	0.60	0.71	0.78	1.01	0.69***(*4.34*)	0.72***(*3.72*)
AG	0.46	0.64	0.58	0.65	0.65	0.64	0.61	0.87	0.86	1.02	0.56***(*3.55*)	0.64***(*3.40*)
OPR	0.31	0.50	0.52	0.55	0.71	0.55	0.59	0.77	0.83	0.94	0.63***(*3.02*)	0.79***(*3.60*)

Table 8: Fama-Macbeth Regression

This table presents the Fama-Macbeth (1973) regression results of month t+1 stock excess return r^i_{t+1} on $\beta^{spc}_{i,t}$ and control variables measured at the end of month t. The "ln(·)" denotes the natural log transformation. OPR* equals OPR if OPR is not missing and 0 otherwise. All independent variables are winsorized at the 0.5% and 99.5% levels every month. The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The sample period (month t) spans from December 1996 to December 2019 and includes only common stocks above the NYSE size 20th cutoff at the end of each month.

	Dependent variable: r^i_{t+1} in percentage			
	(1)	(2)	(3)	(4)
β^{spc}	6.134***	5.914***	5.664***	4.112***
	(3.15)	(3.27)	(3.26)	(3.17)
β^{capm}		-0.005	0.012	-0.095
		(-0.01)	(0.03)	(-0.34)
β^{vix}			3.470	-1.462
			(0.53)	(-0.26)
ln(BM)				-0.028
				(-0.34)
ln(SIZE)				-0.096**
				(-2.06)
MOM				0.044
				(0.15)
REV				-1.508**
				(-2.28)
ILLIQ				0.041
				(0.01)
IVOL				-9.047
				(-1.26)
AG				-0.348***
				(-4.11)
OPR*				0.956**
				(2.38)
Avg(adj. R^2)	0.3%	4.7%	5.0%	9.7%
Obs.	531,458	531,458	531,458	480,974

Table 9: Predicting Stock Returns at Longer Horizons

This table presents the Fama-MacBeth (1973) regression coefficients of r^i_{t+h} on $\beta^{spc}_{i,t}$, where r^i_{t+h} represents the h-months stock excess return from months t to t+h. Each column corresponds to one of the four specifications outlined in Table 8. For simplicity, the coefficients on the intercept and control variables are omitted. All independent variables are winsorized at the 0.5% and 99.5% levels on a monthly basis. The t-statistics, reported in parentheses, are adjusted using Newey and West's (1987) methodology with six lags. The sample period spans from December 1996 to December 2019 and includes only common stocks above the NYSE size 20th cutoff at the end of each month.

	Fama-Macbeth regression coefficients of r^i_{t+h} (in percentage) on $\beta^{spc}_{i,t}$			
h (months)	(1)	(2)	(3)	(4)
3	11.517**	12.272***	12.071***	8.555***
	(2.45)	(2.88)	(2.89)	(2.73)
6	17.021**	20.051***	19.489***	11.132*
	(2.37)	(3.07)	(3.02)	(1.93)
9	16.042	22.536**	21.769**	8.149
	(1.54)	(2.37)	(2.32)	(0.90)
12	22.848*	31.456***	30.962***	11.227
	(1.81)	(2.68)	(2.68)	(1.01)

Table 10: Robustness: Alternative r^{spc}

This table shows the time-series results for alternative model-implied discount rate, with focus on the 1-year predictive horizon. r^{spread}_t is constructed with spc^{spread}_t from the slope of at-the-money put-minus-call implied volatility spread. $r^{interp\_VS}_t$ and $r^{interp\_TR}_t$ are based on the $spc^{interp\_VR}_t$ and $spc^{interp\_TR}_t$, which are the slope of put-call implied volatility ratio at strike $K = Se^{(r^f - q)\tau}$, with the implied volatility interpolated from Volatility Surface or option trading data, respectively. r^{ex10}_t and $r^{ex>1Y}_t$ are from spc^{ex10}_t and $spc^{ex>1Y}_t$, which exclude the 10-day or above 1-year maturity in the construction of *spc*. The Newey and West (1987) t-statistics with 12 lags are reported in parenthesis. The data ranges from January 1996 to December 2019.

	$r^M_{t+1Y} - r^f_t = a + b \times (X_t - r^f_t) + \varepsilon_t$					
X_t	a	b	Adj. R^2	$p(a=0, b=1)$	R^2_{oos}	N
r^{spread}_t	0.002	1.008***	11.74%	0.988	13.43%	288
	(0.06)	(5.32)				
$r^{interp\_VS}_t$	0.043	0.720***	7.02%	0.211	5.94%	288
	(1.32)	(4.53)				
$r^{interp\_TR}_t$	0.052	0.476***	5.85%	0.000	-0.92%	288
	(1.64)	(4.09)				
r^{ex10}_t	0.014	0.871***	9.44%	0.743	10.98%	288
	(0.38)	(4.83)				
$r^{ex>1Y}_t$	0.054*	0.230***	5.12%	0.000	-54.67%	288
	(1.71)	(4.21)				

Table 11: Robustness: Alternative β^{spc}

This table summarizes the Fama-MacBeth (1973) regression coefficients of month t+1 stock excess return on alternative slope betas at the end of month t, with each column representing one of the four specifications in Table 8. In Panel A, we estimate slope beta as stock's exposure to the alternative r^{spc} in Table 10, denoted by β^{spc}_{spread}, $\beta^{spc}_{interp\_VS}$, $\beta^{spc}_{interp\_TR}$, β^{spc}_{ex10}, and $\beta^{spc}_{ex>1Y}$, respectively. In Panel B, we estimate slope beta as stock's exposure to r^{spc} innovations rather than r^{spc} levels, where the r^{spc} innovations are residuals from AR(1) model using full sample data ($\beta^{spc}_{Full\_AR}$), rolling 12-month daily data ($\beta^{spc}_{Roll\_AR}$), or expanding window data ($\beta^{spc}_{Expand\_AR}$). As in the main text, the slope betas in Panel A and B are estimated with the Carhart 4 factors as controls. Panel C estimates the slope betas with different factor returns as controls. The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The month t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above the NYSE size 20th cutoff at the end of each month.

	Dependent variable: r^i_{t+1} in percentage			
	(1)	(2)	(3)	(4)
Panel A: Slope beta from alternative r^{spc}				
β^{spc}_{spread}	5.202***	5.051***	4.735***	3.336**
	(2.65)	(2.69)	(2.64)	(2.43)
$\beta^{spc}_{interp\_VS}$	6.326***	6.099***	5.830***	4.148***
	(3.07)	(3.18)	(3.16)	(2.99)
$\beta^{spc}_{interp\_TR}$	8.303***	7.859***	7.551***	4.829***
	(3.27)	(3.35)	(3.30)	(2.72)
β^{spc}_{ex10}	5.596***	5.368***	5.147***	3.771***
	(2.96)	(3.07)	(3.06)	(3.07)
$\beta^{spc}_{ex>1Y}$	14.674***	14.658***	14.086***	10.175***
	(3.32)	(3.46)	(3.39)	(3.11)
Panel B: Slope beta from r^{spc} innovations				
$\beta^{spc}_{Full\_AR}$	4.098***	3.651**	3.509**	2.371**
	(2.50)	(2.38)	(2.36)	(2.06)
$\beta^{spc}_{Roll\_AR}$	3.737**	3.715**	3.618**	2.543**
	(2.39)	(2.46)	(2.46)	(2.28)
$\beta^{spc}_{Expand\_AR}$	4.234**	3.892**	3.739**	2.598**
	(2.59)	(2.52)	(2.51)	(2.27)
Panel C: Slope beta from alternative factor controls				
β^{spc}_{MKT}	4.814**	5.076**	4.866**	3.635***
	(2.06)	(2.52)	(2.44)	(2.74)
β^{spc}_{FF3}	5.094**	5.283**	5.096**	3.604**
	(2.24)	(2.49)	(2.49)	(2.45)
β^{spc}_{FF5}	4.131*	4.528**	4.306**	3.308**
	(1.89)	(2.21)	(2.17)	(2.25)
β^{spc}_{FF6}	5.686***	5.635***	5.368***	4.045***
	(2.81)	(3.00)	(2.95)	(2.90)
β^{spc}_{Q5}	3.458*	3.636**	3.362**	2.440*
	(1.93)	(2.08)	(1.97)	(1.93)

Table 12: spc_i from Individual Stock Options

This table reports the results of the Fama-Macbeth (1973) regression of month t+1 stock excess return r^i_{t+1} on the spc_i, β^{spc}_i, and control variables measured at the end of month t. The spc_i is the slope of the at-the-money put-call implied volatility ratio extracted from individual stock options. The "ln(·)" denotes the natural log transformation. OPR* equals OPR if OPR is not missing and 0 otherwise. All the independent variables are winsorized at 0.5% and 99.5% levels every month. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with six lags. The month t ranges from December 1996 to December 2019, and the sample includes only those common stocks above the NYSE size 20th cutoff at the end of each month.

	Dependent variable: r^i_{t+1} in percentage									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
spc_i	4.089**	4.050***	3.890***	3.741***	-1.006	4.060**	4.066***	3.914***	3.754***	-0.992
	(2.31)	(3.21)	(3.13)	(3.42)	(-0.95)	(2.28)	(3.19)	(3.11)	(3.41)	(-0.94)
β^{spc}						5.457***	5.267***	5.024***	3.491***	3.418**
						(2.71)	(2.87)	(2.87)	(2.62)	(2.55)
β^{capm}		0.009	0.039	-0.071	-0.083		0.021	0.047	-0.058	-0.070
		(0.02)	(0.11)	(-0.25)	(-0.29)		(0.06)	(0.13)	(-0.20)	(-0.24)
β^{vix}			4.087	-2.530	-1.970			4.063	-1.851	-1.271
			(0.57)	(-0.39)	(-0.31)			(0.57)	(-0.29)	(-0.20)
ln(BM)				0.001	-0.005				-0.001	-0.007
				(0.01)	(-0.06)				(-0.01)	(-0.08)
ln(SIZE)				-0.084*	-0.081				-0.084	-0.081
				(-1.65)	(-1.61)				(-1.63)	(-1.61)
MOM				-0.008	0.013				-0.032	-0.010
				(-0.03)	(0.04)				(-0.11)	(-0.03)
REV				-1.404**	-1.133*				-1.359**	-1.091
				(-2.11)	(-1.70)				(-2.05)	(-1.64)
ILLIQ				9.617	9.922				9.106	9.444
				(0.91)	(0.91)				(0.87)	(0.88)
IVOL				-9.364	-9.218				-9.216	-9.100
				(-1.33)	(-1.36)				(-1.32)	(-1.36)
AG				-0.348***	-0.339***				-0.358***	-0.350***
				(-4.16)	(-4.15)				(-4.28)	(-4.27)
OPR*				1.132***	1.079**				1.101***	1.046**
				(2.66)	(2.57)				(2.60)	(2.50)
IVSKEW					-0.923**					-0.944**
					(-2.25)					(-2.32)
IVSPREAD					-4.297***					-4.286***
					(-5.45)					(-5.43)
RNS					0.167**					0.160**
					(2.20)					(2.16)
Avg(adj. R^2)	0.1%	4.6%	5.0%	9.8%	10.0%	0.5%	4.8%	5.2%	10.0%	10.2%
Obs.	452,469	452,469	452,469	414,983	414,980	452,469	452,469	452,469	414,983	414,980

Internet Appendix

A Time-series Results with Daily Data

Here, we repeat the time-series analysis in Section 2.2 using daily data. Figure A1 plots the daily model-implied discount rate r^{spc} under the constant parameter version, from which we observe significant variations over time. In fact, Table A1 shows that its first-order autocorrelation is only about 0.53.

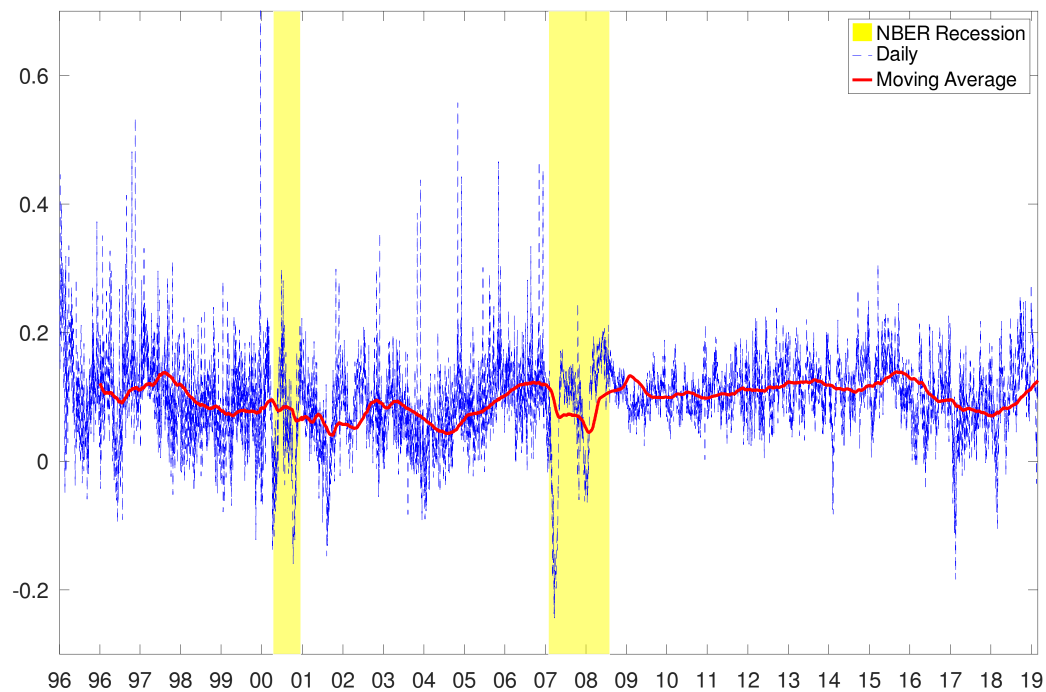

Figure A1: Time series of r_t^{spc} (Daily Data). This figure plots the daily model-implied discount rate r^{spc} under constant parameters in equation (10) of the main text, with the solid line representing its 252-day moving average. The shaded areas indicate NBER recessions. The date range is from January 4, 1996, to December 31, 2019.

Next, we run the predictive regression of future 1-year market excess return $r_{t+1Y}^M - r_t^f$ on the model-implied premium $r^{spc} - r_t^f$ under different parameter choices as Table 1 in the main text

$$r_{t+1Y}^M - r_t^f = a + b \times (r_t^{spc} - r_t^f) + \varepsilon_t \tag{A-1}$$

where r_{t+1Y}^M is calculated by compounding daily market returns over the next 252 trading days from t to t+252. The daily market return data is from Kenneth French's website (Rm-Rf + Rf). The annual risk-free rate r_t^f is the 1-year risk-free rate at date t from linear interpolation of the zero-coupon yield curve data in OptionMetrics. The regression is run at daily frequency and we adjust the t-statistics based on Newey and West (1987) with 252 lags.

Table A1: Model-implied Discount Rate and Future Stock Market Returns (Daily Data)

Panel A shows the summary statistics of the daily model-implied discount rate r_t^{spc}, model-implied premium $r_t^{spc} - r_t^f$ under constant parameters in equation (10) of the main text, and the corresponding future 1-year market excess return $r_{t+1Y}^M - r_t^f$. The "AR1" in the last column presents the first-order autocorrelation coefficient. Panel B reports the in-sample predictive regression results of future 1-year market excess returns on the model-implied 1-year premium: $r_{t+1Y}^M - r_t^f = a + b \times (r_t^{spc} - r_t^f) + \varepsilon_t$ and the out-of-sample R-squared (R_{oos}^2) of model-implied forecasts under different parameter choices, as in Table 1 of the main text. The regression is run at daily frequency, and the t-stats in parentheses are adjusted according to Newey and West (1987) with 252 lags. We also report the p-value of the Wald test for the null hypothesis of (a=0, b=1). The date range is from January 4, 1996, to December 31, 2019.

Panel A: Summary statistics

	Obs.	Mean	Std.	Min	P25	P50	P75	Max	Skew	AR1
r_t^{spc} (%)	6,040	9.73	6.74	-24.37	6.28	10.06	13.50	108.64	0.42	0.53
$r_t^{spc} - r_t^f$ (%)	6,040	6.89	7.21	-27.11	2.81	7.41	11.37	102.25	0.10	0.59
$r_{t+1Y}^M - r_t^f$ (%)	6,040	7.63	17.73	-50.10	0.56	10.82	18.94	73.61	-0.74	0.99

Panel B: Results of predictive regression: $r_{t+1Y}^M - r_t^f = a + b \times (r_t^{spc} - r_t^f) + \varepsilon_{t+1}$

Parameter choice	a	b	Adj. R^2	$p(a=0, b=1)$	R_{oos}^2
$g = 3.18\%, q = 4.93\%, \sigma^c = 20.47\%$	0.039	0.544***	4.88%	0.021	3.87%
(Main specification)	(1.06)	(2.92)			
$g = 3.18\%, q = 4.93\%$, varying σ^c	0.038	0.573***	5.21%	0.041	4.51%
	(1.05)	(3.09)			
varying $g, q = 4.93\%, \sigma^c = 20.47\%$	0.038	0.541***	4.86%	0.019	3.85%
	(1.04)	(2.89)			
varying $g, q = 4.93\%$, varying σ^c	0.037	0.570***	5.21%	0.038	4.52%
	(1.02)	(3.05)			
$g = 3.18\%$, varying $q, \sigma^c = 20.47\%$	0.041	0.517***	4.76%	0.007	2.97%
	(1.16)	(2.99)			
$g = 3.18\%$, varying q and σ^c	0.040	0.548***	5.12%	0.017	3.72%
	(1.15)	(3.17)			
varying g and $q, \sigma^c = 20.47\%$	0.041	0.515***	4.76%	0.006	2.96%
	(1.13)	(2.96)			
varying $g, q,$ and σ^c	0.040	0.545***	5.11%	0.015	3.75%
	(1.12)	(3.13)			

Panel B of Table A1 shows that, regardless of parameter choices, the coefficients on $r_t^{spc} - r_t^f$ are always significantly positive and not far away from one while the regression intercepts are always indistinguishable from zero. The p-values for the equivalence test are lower than those under monthly data in Table 1, perhaps due to the severe overlapping issues in daily data. In addition, the out-of-sample R squares are all positive.

In Panel A of Table A2, we examine the predictive ability of r^{spc} for future stock market return at different horizons

$$r^M_{t+h} - r^f_t = a + b \times (r^{spc}_t - r^f_t) + \varepsilon_t \tag{A-2}$$

where r^M_{t+h} is the annualized market return over the next h trading days from month t+1 to t+h (both inclusive) and r^f_t is again the annual risk-free rate at date t. The t-statistics are based on Newey and West (1987) with h lags. We can see that the coefficient on $r^{spc}_t - r^f_t$ is significantly positive for the 3-month to 2-year horizons.

Finally, in Panel B of Table A2, we further control for the established daily option-based time-series predictors in literature, including RBnd (Martin, 2017), which measures the annualized lower bound of expected market excess return at different horizons, AIVS (Han and Li, 2021), which is the cross-sectional average of call-put implied volatility spread from equity options with a 30-day maturity, VSk (Atilgan, Bali and Demirtas, 2015) which denotes the implied volatility difference between out-of-money put and at-the-money call option with a 30-day maturity for S&P 500 index option, and the related VSpd (or VR), which is the implied volatility difference (or ratio minus 1) between at-the-money put and call option with 30-day maturity for S&P 500 index option. We include VSpd and VR separately due to their high correlation.

With the above controls, the coefficients on $r^{spc}_t - r^f_t$ remain significantly positive at the 6-month, 1-year, and 2-year horizons, which implies that $r^{spc}_t - r^f_t$ carries additional information beyond these control variables. As for the controls, the coefficients on RBnd are close to 1, consistent with Martin (2017). AIVS has a significantly positive coefficient at short horizons from 1 to 6 months, consistent with Han and Li (2021). However, $r^{spc}_t - r^f_t$ emerges as the dominant predictor for longer time frames. Although Atilgan, Bali and Demirtas (2015) highlight VSk's predictive capability for a very short horizon of one week, the coefficients on VSk in our horizons are insignificant. Additionally, VSpd and VR possess only marginal predictive ability, which is much weaker than that of $r^{spc}_t - r^f_t$.

Overall, our time-series results in the Section 2.3 is robust to daily data.

Table A2: Predictive Regression with Controls and Other Horizons (Daily Data)

This table presents the regression results of future stock market excess returns at different horizons $r^M_{t+h} - r^f_t$ on $r^{spc}_t - r^f_t$, with and without control variables. The regression is run at daily frequency. $r^M_{t+h} - r^f_t$ is the annualized h-day market excess return from t to t+h, where the horizon h can be 21, 63, 126, 252, or 504 trading days. Among the control variables in Panel B, RBnd is the annualized lower bound of expected market excess return at corresponding horizons (Martin, 2017), AIVS is the cross-sectional average of at-the-money call-put implied volatility spread at 30-day maturity from equity options (Han and Li, 2021), VSk is the implied volatility difference between out-of-the-money put and at-the-money call at 30-day maturity for S&P 500 index options (Atilgan, Bali and Demirtas, 2015), and VSpd (VR) is the implied volatility difference (ratio minus 1) between at-the-money put and call at 30-day maturity for S&P 500 index options. In both panels, the Newey and West (1987) t-statistics with lags equal to the predictive horizon are in parentheses. The date range is from January 4, 1996, to December 31, 2019.

Panel A: Results of predictive regression: $r^M_{t+h} - r^f_t = a + b \times (r^{spc}_t - r^f_t) + \varepsilon_{t+h}$

	(1)	(2)	(3)	(4)	(5)
h	21D	63D	126D	252D	504D
a	0.062*	0.046	0.042	0.039	0.045
	(1.75)	(1.48)	(1.46)	(1.06)	(1.24)
b	0.233	0.387*	0.437**	0.544***	0.531***
	(0.83)	(1.85)	(2.45)	(2.92)	(3.02)
Adj. R^2	0.07%	0.72%	1.79%	4.88%	6.93%
$p(a = 0, b = 1)$	0.024	0.014	0.006	0.021	0.021
N	6,040	6,040	6,040	6,040	6,040

Panel B: Results of predictive regression: $r^M_{t+h} - r^f_t = a + b \times (r^{spc}_t - r^f_t) + \sum_j control_{j,t} + \varepsilon_{t+h}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
h	21D	63D	126D	252D	504D	21D	63D	126D	252D	504D
a	0.083	-0.073	-0.083	-0.063	-0.044	0.070	-0.068	-0.087	-0.064	-0.043
	(0.88)	(-0.88)	(-1.19)	(-0.83)	(-0.57)	(0.74)	(-0.84)	(-1.28)	(-0.84)	(-0.57)
b	0.310	0.436	0.607**	0.695***	0.609***	0.354	0.463	0.677**	0.757***	0.661**
	(0.71)	(1.38)	(2.46)	(2.90)	(2.60)	(0.76)	(1.34)	(2.49)	(2.82)	(2.46)
RBnd	1.076	0.131	2.183*	1.507	0.198	1.032	0.181	2.183*	1.516	0.192
	(0.72)	(0.08)	(1.68)	(1.17)	(0.13)	(0.68)	(0.11)	(1.73)	(1.22)	(0.12)
AIVS	4.225***	2.318**	1.636**	0.749	0.880	4.153***	2.343**	1.600**	0.730	0.864
	(3.08)	(2.31)	(2.02)	(1.64)	(1.52)	(3.08)	(2.35)	(1.99)	(1.61)	(1.52)
VSk	-0.526	1.545	0.432	0.457	1.010	-0.375	1.429	0.424	0.413	0.970
	(-0.35)	(1.15)	(0.41)	(0.54)	(1.53)	(-0.24)	(1.11)	(0.42)	(0.52)	(1.53)
VSpd	0.949	-1.836	-1.582	-2.001*	-1.856*					
	(0.51)	(-1.30)	(-1.49)	(-1.74)	(-1.81)					
VR						0.039	-0.323	-0.386*	-0.433*	-0.391*
						(0.12)	(-1.17)	(-1.87)	(-1.82)	(-1.69)
Adj. R^2	1.29%	3.70%	9.27%	11.05%	12.68%	1.26%	3.67%	9.65%	11.57%	13.21%
N	6,040	6,040	6,040	6,040	6,040	6,040	6,040	6,040	6,040	6,040

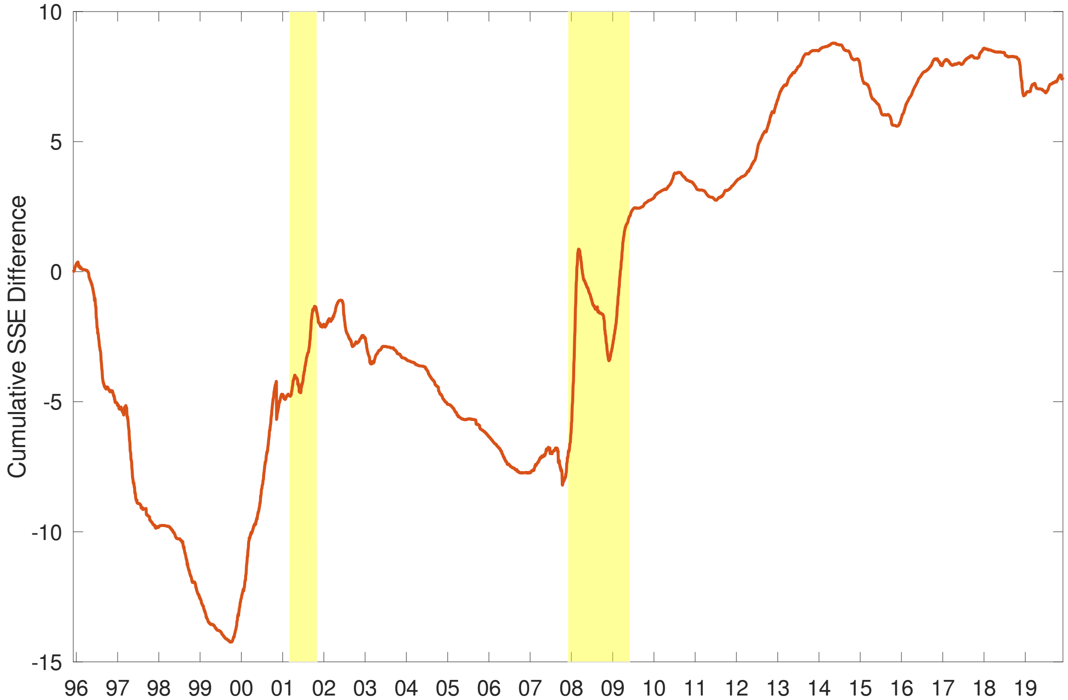

Figure A2: Cumulative Out-of-Sample Out-Performance of Model-Implied Forecast (Daily Data). This figure plots the cumulative difference of the sum of squared prediction errors (SSE) between the historical mean and model-implied forecast (constant parameter version) for future 1-year market excess returns using daily data. The date range is from January 4, 1996, to December 31, 2019.

B Open-Source Asset Pricing Data

The open-source asset pricing website maintained by Chen and Zimmermann provides a convenient way to obtain data for a comprehensive list of stock characteristics. To obtain the monthly data of stock returns and control variables, we run the "dl_signals_add_crsp.R" with the data release set to March 2022. The default output contains 5,115,815 observations. However, stock returns are not included in the default output. To obtain the monthly stock returns, we add the following line (line 131) to the original code:

```
    # NOTE THESE ARE SIGNED!
    # from me: change the following to add ret and me to output
    crspsignal = crspm2 %>%
    transmute(
      permno
      , yyyymm
      , ret
      , me
      , STreversal = -1*if_else(is.na(ret), 0, ret)
      , Price = -1*log(abs(prc))
      , Size = -1*log(me)
    )
```

Figure B1: Changes to Chen and Zimmermann's code.

The monthly stock returns are then used to get the one-month-ahead returns in the cross-sectional tests. Note that the accounting-related variables in the open-source dataset are already matched to each month's end by considering lags and the monthly stock returns are already adjusted for delisting.

In the followings, we provide detailed descriptions of the control variables we use in the cross-sectional analysis and how we obtain them from the open-source asset pricing dataset.

- β^{capm}: CAPM beta, estimated by regressing daily stock excess return on daily market excess return over the past 12 months, with at least 200 observations. Here, the 12-month window matches that of β^{spc} estimation.

- β^{vix}: the volatility beta in Ang, Hodrick, Xing and Zhang (2006), defined as the exposure to daily VXO changes while controlling for market excess return. It is estimated using the past one-month daily data.

- BM: book-to-market ratio in Fama and French (1992), defined as book equity divided by December market capitalization.

- SIZE: the market capitalization in millions of dollars at each month's end.

- MOM: momentum in Jegadeesh and Titman (1993), defined as the return over the past 12 months while skipping the most recent month.

- REV: reversal in Jegadeesh (1990), defined as the return over the past month.

- ILLIQ: illiquidity in Amihud (2002), defined as daily absolute return divided by daily dollar trading volume (in millions of dollars), averaged over the past 12 months.
- IVOL: idiosyncratic volatility in Ang, Hodrick, Xing and Zhang (2006), defined as the standard deviation of the residual returns with respect to the Fama-French three-factor model. It is estimated using daily data in the past month.
- AG: Annual growth rate of total assets in Fama and French (2015).
- OPR: R&D-adjusted operating profitability in Ball, Gerakos, Linnainmaa and Nikolaev (2015), defined as revenue minus the cost of goods sold, minus selling, general, and administrative expenses, plus research and development expense, then divided by total assets.

All the above control variables except β^{capm} are fetched from the open-source dataset with minor modifications described in the following table. For the β^{capm}, we calculate it ourselves since we cannot find the exact correspondence we need,[1] but the results are robust to the beta in the open-source dataset.

Table B1: Control Variables Mapping

This table shows the mapping between the control variables used in this paper and the data library in Chen and Zimmermann (CZ). Note that the characteristics in CZ are signed according to their relationship with future returns, and therefore we need to adjust them back.

This paper	CZ data library	Relation
β^{vix}	betaVIX	$\beta^{vix} = -$betaVIX
BM	BMdec	BM = BMdec; if BM<=0, then set it to missing
SIZE	Size	SIZE = exp($-$Size)/1000000
MOM	Mom12	MOM = Mom12
REV	STreversal	REV = $-$STreversal/100
ILLIQ	Illiquidity	ILLIQ = Illiquidity*1000000
IVOL	IdioVol3F	IVOL = -IdioVol3F
AG	AssetGrowth	AG = -AssetGrowth
OPR	OperProfRD	OPR = OperProfRD

C Alternative Stock Samples

In the following tables, we repeat the main cross-sectional analysis in Section 3, including univariate portfolio analysis, dependent bivariate sort, and Fama-Macbeth regression, for the all-stocks sample

[1] The "beta" field in the open source dataset is the rolling 60-month regression coefficient of monthly stock excess return on equal-weighted market return rather than rolling 12-month daily data and value-weighted market return.

and above-NYSE-size-50th sample.

Table C1: Portfolio Returns Sorted by β^{spc} (All-Stocks Sample)

This table presents the results of a univariate portfolio analysis for the all-stocks sample. At the end of month t, stocks are sorted into ten groups based on the ascending order of β^{spc}. The table reports the time-series averages of each portfolio's month t+1 excess returns (Raw) and the month t+1 high-minus-low returns (H-L), as well as their alphas adjusted for different factor models, including the CAPM, Fama-French three-factor and five-factor models (FF3 and FF5), Carhart four-factor model (FFC), Fama-French five-factor model plus momentum (FF6), and the Q5 model in Hou, Mo, Xue and Zhang (2021). The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The month-end t ranges from December 1996 to December 2019, and the sample includes all common stocks listed in NYSE, NASDAQ, and AMEX at the end of each month.

Panel A: Equal-weighted return and α (%)

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw	0.31	0.61	0.75	0.77	0.82	0.95	0.99	0.97	1.10	0.90	0.60***
	(0.55)	(1.50)	(2.16)	(2.37)	(2.66)	(2.97)	(2.97)	(2.60)	(2.62)	(1.65)	(3.70)
CAPM	-0.61	-0.16	0.07	0.14	0.22	0.34	0.35	0.29	0.35	-0.01	0.60***
	(-1.89)	(-0.81)	(0.42)	(0.82)	(1.20)	(1.88)	(1.88)	(1.36)	(1.43)	(-0.02)	(3.68)
FF3	-0.60	-0.20	0.04	0.09	0.17	0.29	0.30	0.24	0.32	-0.01	0.59***
	(-2.67)	(-1.83)	(0.41)	(1.08)	(1.65)	(2.87)	(3.02)	(1.84)	(2.00)	(-0.04)	(3.51)
FFC	-0.33	-0.04	0.17	0.20	0.27	0.39	0.42	0.36	0.51	0.32	0.64***
	(-1.27)	(-0.30)	(1.92)	(2.20)	(2.61)	(3.87)	(4.04)	(2.88)	(3.35)	(1.28)	(3.87)
FF5	-0.20	-0.07	0.07	0.09	0.13	0.26	0.26	0.26	0.44	0.34	0.54***
	(-0.82)	(-0.54)	(0.77)	(0.96)	(1.17)	(2.38)	(2.51)	(1.83)	(2.40)	(1.20)	(3.15)
FF6	-0.02	0.04	0.17	0.17	0.20	0.33	0.34	0.35	0.58	0.57	0.58***
	(-0.07)	(0.27)	(1.89)	(1.85)	(2.07)	(3.39)	(3.62)	(2.78)	(3.65)	(2.16)	(3.56)
Q5	0.15	0.18	0.28	0.22	0.25	0.38	0.36	0.38	0.64	0.75	0.60***
	(0.48)	(0.96)	(2.08)	(1.67)	(1.69)	(2.83)	(2.80)	(2.42)	(3.17)	(2.42)	(3.26)

Panel B: Value-weighted return and α (%)

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw	-0.04	0.48	0.54	0.63	0.60	0.63	0.73	0.89	0.91	1.01	1.04***
	(-0.07)	(1.33)	(1.86)	(2.32)	(2.27)	(2.31)	(2.87)	(2.86)	(2.42)	(1.99)	(3.90)
CAPM	-0.98	-0.22	-0.07	0.05	0.02	0.05	0.15	0.22	0.14	-0.02	0.96***
	(-4.59)	(-1.49)	(-0.85)	(0.66)	(0.24)	(0.66)	(1.77)	(1.97)	(1.08)	(-0.05)	(3.19)
FF3	-0.96	-0.21	-0.08	0.04	0.01	0.04	0.14	0.21	0.15	0.03	0.99***
	(-4.83)	(-1.48)	(-1.00)	(0.65)	(0.08)	(0.52)	(1.66)	(1.91)	(1.20)	(0.11)	(3.37)
FFC	-0.88	-0.17	-0.11	0.02	0.00	0.04	0.16	0.26	0.24	0.22	1.10***
	(-4.49)	(-1.27)	(-1.42)	(0.24)	(0.02)	(0.51)	(1.91)	(2.26)	(1.91)	(1.01)	(3.87)
FF5	-0.67	-0.18	-0.15	0.01	-0.06	-0.01	0.06	0.23	0.23	0.37	1.05***
	(-3.97)	(-1.11)	(-1.64)	(0.16)	(-0.84)	(-0.12)	(0.77)	(2.06)	(1.66)	(1.46)	(3.28)
FF6	-0.63	-0.15	-0.17	-0.01	-0.06	-0.01	0.08	0.26	0.30	0.50	1.13***
	(-3.51)	(-0.97)	(-1.95)	(-0.10)	(-0.83)	(-0.08)	(1.06)	(2.37)	(2.17)	(2.19)	(3.74)
Q5	-0.58	-0.05	-0.17	-0.02	-0.13	-0.01	0.05	0.20	0.25	0.60	1.18***
	(-2.91)	(-0.35)	(-1.87)	(-0.32)	(-1.83)	(-0.09)	(0.55)	(1.75)	(1.82)	(2.29)	(3.42)

Table C2: Portfolio Returns Sorted by β^{spc}: Control for Other Variables (All-Stocks Sample)

This table presents the results of a bivariate portfolio analysis. The analysis is conducted as follows: at the end of month t, stocks are sorted into ten groups based on each control variable separately. Within each control group, stocks are further sorted into ten subgroups in ascending order of β^{spc}. For each of the resulting 10×10 portfolios, equal-weighted and value-weighted excess returns are calculated for the following month, t+1. The table reports the average month t+1 return for each β^{spc} group, which is computed as the average return across the ten subgroups sorted by the control variable. These time-series averages are expressed in percentage terms. Additionally, the table includes the high-minus-low return (H-L), its alpha (FF6 α) adjusted for the Fama-French five-factor plus momentum model, and their corresponding t-statistics in parentheses. The t-statistics are adjusted using the method proposed by Newey and West (1987) with six lags. The analysis covers the period from December 1996 to December 2019, and the sample includes all common stocks listed in NYSE, NASDAQ, and AMEX at the end of each month.

Panel A: Equal-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	FF6 α
β^{capm}	0.32	0.63	0.71	0.77	0.85	0.93	0.97	0.94	1.12	0.93	0.61***(*3.70*)	0.59***(*3.79*)
β^{vix}	0.36	0.63	0.80	0.78	0.83	0.93	0.95	0.97	0.97	0.97	0.61***(*4.27*)	0.59***(*4.09*)
BM	0.45	0.79	0.80	0.84	0.92	0.96	0.98	1.03	1.13	1.02	0.57***(*3.86*)	0.58***(*3.69*)
SIZE	0.30	0.59	0.82	0.80	0.91	0.97	0.93	1.05	1.01	0.79	0.49***(*3.16*)	0.51***(*3.16*)
MOM	0.41	0.77	0.72	0.81	0.81	0.97	0.90	1.01	0.94	0.91	0.50***(*3.82*)	0.53***(*3.85*)
REV	0.25	0.73	0.73	0.87	0.85	0.90	1.04	0.92	1.01	0.88	0.63***(*4.13*)	0.66***(*4.31*)
ILLIQ	0.29	0.64	0.77	0.78	0.93	0.94	0.99	1.00	1.10	0.81	0.52***(*3.35*)	0.54***(*3.47*)
IVOL	0.49	0.66	0.76	0.78	0.86	0.90	0.83	0.95	0.95	0.99	0.50***(*3.76*)	0.52***(*4.01*)
AG	0.40	0.72	0.84	0.84	0.89	0.96	0.98	1.06	1.12	0.96	0.56***(*3.90*)	0.57***(*3.91*)
OPR	0.43	0.73	0.78	0.79	0.82	0.98	0.84	1.03	1.06	0.98	0.55***(*3.35*)	0.60***(*3.57*)

Panel B: Value-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	FF6 α
β^{capm}	0.32	0.54	0.67	0.56	0.69	0.68	0.80	0.84	0.85	0.92	0.60***(*3.39*)	0.58***(*2.99*)
β^{vix}	0.28	0.46	0.62	0.70	0.68	0.67	0.66	0.86	0.87	0.82	0.54***(*2.70*)	0.52***(*2.04*)
BM	0.16	0.60	0.65	0.67	0.72	0.70	0.72	0.96	0.99	1.20	1.04***(*5.05*)	1.08***(*4.80*)
SIZE	0.25	0.52	0.75	0.73	0.86	0.92	0.90	0.98	0.92	0.76	0.50***(*3.19*)	0.52***(*3.07*)
MOM	0.04	0.48	0.53	0.66	0.47	0.70	0.59	0.75	0.72	0.75	0.71***(*3.88*)	0.73***(*3.35*)
REV	0.32	0.56	0.62	0.67	0.65	0.58	0.76	0.96	0.99	1.01	0.70***(*3.49*)	0.77***(*3.33*)
ILLIQ	0.20	0.55	0.78	0.70	0.85	0.83	0.92	0.90	0.98	0.79	0.59***(*3.50*)	0.51***(*3.12*)
IVOL	0.25	0.45	0.62	0.52	0.50	0.62	0.55	0.60	0.76	0.86	0.61***(*3.30*)	0.66***(*2.92*)
AG	0.29	0.63	0.54	0.65	0.73	0.69	0.70	1.03	0.94	1.12	0.83***(*3.89*)	0.93***(*3.81*)
OPR	0.16	0.32	0.40	0.53	0.54	0.58	0.52	0.76	0.84	0.72	0.56** (*2.15*)	0.70** (*2.49*)

Table C3: Fama-Macbeth Regression (All-Stocks Sample)

This table presents the Fama-Macbeth (1973) regression results of month t+1 stock excess return r^i_{t+1} on $\beta^{spc}_{i,t}$ and control variables measured at the end of month t. The "ln(·)" denotes the natural log transformation. OPR* equals OPR if OPR is not missing and 0 otherwise. All independent variables are winsorized at the 0.5% and 99.5% levels every month. The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The sample period (month t) spans from December 1996 to December 2019, and the sample includes all common stocks listed in NYSE, NASDAQ, and AMEX at the end of each month.

	Dependent variable: r^i_{t+1} in percentage			
	(1)	(2)	(3)	(4)
β^{spc}	4.830***	4.997***	4.799***	3.074***
	(3.93)	(4.05)	(3.94)	(3.35)
β^{capm}		-0.156	-0.148	0.015
		(-0.67)	(-0.64)	(0.07)
β^{vix}			-2.438	-1.674
			(-0.47)	(-0.44)
ln(BM)				-0.017
				(-0.18)
ln(SIZE)				-0.120**
				(-2.34)
MOM				0.065
				(0.22)
REV				-2.245***
				(-4.06)
ILLIQ				0.029***
				(4.31)
IVOL				-22.753***
				(-4.71)
AG				-0.627***
				(-6.13)
OPR*				1.701***
				(5.88)
Avg(adj. R^2)	0.1%	1.9%	2.0%	5.6%
Obs.	1,249,256	1,249,256	1,249,256	1,082,408

Table C4: Portfolio Returns Sorted by β^{spc} (Above-NYSE-Size-50th Sample)

This table presents the results of a univariate portfolio analysis for the above-NYSE-size-50th sample. At the end of month t, stocks are sorted into ten groups based on the ascending order of β^{spc}. The table reports the time-series averages of each portfolio's month t+1 excess returns (Raw) and the month t+1 high-minus-low returns (H-L), as well as their alphas adjusted for different factor models, including the CAPM, Fama-French three-factor and five-factor models (FF3 and FF5), Carhart four-factor model (FFC), Fama-French five-factor model plus momentum (FF6), and the Q5 model in Hou, Mo, Xue and Zhang (2021). The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The month-end t ranges from December 1996 to December 2019, and the sample includes only those common stocks above the NYSE 50th size cutoff at the end of each month.

Panel A: Equal-weighted return and α (%)

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw	0.39	0.65	0.61	0.77	0.75	0.72	0.78	0.83	0.86	0.83	0.45**
	(0.91)	(1.98)	(2.07)	(2.76)	(2.72)	(2.63)	(2.86)	(2.97)	(2.61)	(2.06)	(2.44)
CAPM	-0.45	-0.04	-0.02	0.16	0.16	0.13	0.18	0.21	0.15	-0.04	0.41*
	(-2.58)	(-0.31)	(-0.16)	(1.24)	(1.12)	(1.11)	(1.56)	(1.71)	(1.47)	(-0.22)	(1.93)
FF3	-0.45	-0.06	-0.06	0.12	0.12	0.09	0.15	0.17	0.13	-0.01	0.44**
	(-3.04)	(-0.58)	(-0.60)	(1.40)	(1.21)	(1.07)	(1.73)	(1.94)	(1.53)	(-0.07)	(2.09)
FFC	-0.41	-0.04	-0.03	0.12	0.13	0.10	0.14	0.20	0.16	0.11	0.52**
	(-2.90)	(-0.37)	(-0.37)	(1.35)	(1.32)	(1.18)	(1.53)	(2.23)	(1.93)	(0.97)	(2.59)
FF5	-0.25	-0.14	-0.17	0.03	-0.04	-0.02	0.02	0.06	0.12	0.22	0.48**
	(-1.81)	(-1.32)	(-1.78)	(0.35)	(-0.39)	(-0.24)	(0.23)	(0.86)	(1.30)	(1.65)	(2.17)
FF6	-0.23	-0.12	-0.15	0.04	-0.02	-0.01	0.02	0.09	0.14	0.30	0.53**
	(-1.70)	(-1.12)	(-1.63)	(0.37)	(-0.26)	(-0.07)	(0.20)	(1.16)	(1.61)	(2.48)	(2.54)
Q5	-0.07	-0.02	-0.07	0.05	0.01	0.04	0.03	0.08	0.17	0.43	0.50**
	(-0.54)	(-0.15)	(-0.64)	(0.51)	(0.09)	(0.47)	(0.42)	(0.99)	(1.98)	(2.77)	(2.21)

Panel B: Value-weighted return and α (%)

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw	0.36	0.63	0.52	0.64	0.63	0.53	0.61	0.71	0.80	0.93	0.57***
	(0.91)	(1.98)	(1.87)	(2.44)	(2.31)	(1.92)	(2.32)	(2.79)	(2.32)	(2.31)	(2.98)
CAPM	-0.38	0.00	-0.07	0.06	0.07	-0.04	0.06	0.10	0.11	0.09	0.46**
	(-2.45)	(0.01)	(-0.71)	(0.76)	(0.62)	(-0.41)	(0.60)	(0.90)	(0.76)	(0.55)	(2.26)
FF3	-0.37	-0.00	-0.08	0.06	0.05	-0.05	0.05	0.10	0.13	0.13	0.50**
	(-2.44)	(-0.05)	(-0.92)	(0.73)	(0.55)	(-0.54)	(0.54)	(0.82)	(1.02)	(1.10)	(2.50)
FFC	-0.31	-0.05	-0.11	0.05	0.00	-0.04	0.04	0.12	0.18	0.22	0.53**
	(-2.05)	(-0.45)	(-1.20)	(0.61)	(0.01)	(-0.42)	(0.47)	(1.05)	(1.50)	(1.84)	(2.57)
FF5	-0.26	-0.06	-0.15	0.01	-0.03	-0.08	-0.05	0.09	0.20	0.32	0.59**
	(-1.61)	(-0.54)	(-1.55)	(0.17)	(-0.44)	(-0.95)	(-0.55)	(0.88)	(1.51)	(2.39)	(2.45)
FF6	-0.23	-0.09	-0.16	0.01	-0.06	-0.07	-0.05	0.11	0.23	0.39	0.61**
	(-1.37)	(-0.81)	(-1.70)	(0.14)	(-0.86)	(-0.82)	(-0.54)	(1.05)	(1.88)	(2.91)	(2.53)
Q5	-0.18	-0.07	-0.13	-0.05	-0.14	-0.06	-0.07	0.09	0.20	0.37	0.54**
	(-1.08)	(-0.62)	(-1.36)	(-0.54)	(-1.63)	(-0.68)	(-0.73)	(0.73)	(1.56)	(2.52)	(2.14)

Table C5: Portfolio Returns Sorted by β^{spc}: Control for Other Variables (Above-NYSE-Size-50th Sample)

This table presents the results of a bivariate portfolio analysis. The analysis is conducted as follows: at the end of month t, stocks are sorted into ten groups based on each control variable separately. Within each control group, stocks are further sorted into ten subgroups in ascending order of β^{spc}. For each of the resulting 10×10 portfolios, equal-weighted and value-weighted excess returns are calculated for the following month, t+1. The table reports the average month t+1 return for each β^{spc} group, which is computed as the average return across the ten subgroups sorted by the control variable. These time-series averages are expressed in percentage terms. Additionally, the table includes the high-minus-low return (H-L), its alpha (FF6 α) adjusted for the Fama-French five-factor plus momentum model, and their corresponding t-statistics in parentheses. The t-statistics are adjusted using the method proposed by Newey and West (1987) with six lags. The analysis covers the period from December 1996 to December 2019, and the sample includes only those common stocks above the NYSE 50th size cutoff at the end of each month.

Panel A: Equal-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	FF6 α
β^{capm}	0.41	0.59	0.66	0.71	0.72	0.74	0.84	0.84	0.77	0.92	0.51***(*3.03*)	0.50***(*2.73*)
β^{vix}	0.43	0.66	0.64	0.72	0.74	0.70	0.80	0.84	0.81	0.86	0.43***(*2.75*)	0.46** (*2.58*)
BM	0.45	0.66	0.74	0.68	0.78	0.72	0.82	0.78	0.89	0.91	0.47***(*2.69*)	0.50** (*2.39*)
SIZE	0.47	0.52	0.68	0.70	0.77	0.83	0.70	0.85	0.86	0.81	0.35* (*1.80*)	0.47** (*2.19*)
MOM	0.41	0.57	0.71	0.76	0.69	0.77	0.77	0.88	0.83	0.83	0.43***(*2.71*)	0.48***(*2.67*)
REV	0.44	0.69	0.57	0.77	0.73	0.75	0.72	0.79	0.79	0.94	0.50***(*3.34*)	0.55***(*3.19*)
ILLIQ	0.45	0.55	0.63	0.80	0.77	0.69	0.77	0.87	0.84	0.86	0.41** (*2.43*)	0.50** (*2.54*)
IVOL	0.56	0.62	0.57	0.75	0.71	0.73	0.73	0.82	0.80	0.91	0.34** (*2.38*)	0.36** (*2.29*)
AG	0.53	0.65	0.68	0.67	0.73	0.76	0.76	0.89	0.88	0.91	0.38** (*2.24*)	0.40** (*2.00*)
OPR	0.37	0.61	0.62	0.69	0.77	0.66	0.85	0.82	0.87	0.88	0.50***(*2.94*)	0.68***(*3.46*)

Panel B: Value-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	FF6 α
β^{capm}	0.39	0.57	0.64	0.65	0.66	0.63	0.68	0.81	0.66	1.01	0.62***(*3.78*)	0.57***(*2.95*)
β^{vix}	0.40	0.66	0.61	0.54	0.65	0.56	0.67	0.75	0.77	0.88	0.48***(*3.17*)	0.46***(*2.67*)
BM	0.47	0.61	0.57	0.61	0.73	0.62	0.66	0.71	0.89	0.95	0.48***(*2.64*)	0.52** (*2.39*)
SIZE	0.44	0.52	0.68	0.71	0.77	0.82	0.70	0.86	0.83	0.81	0.37* (*1.91*)	0.49** (*2.31*)
MOM	0.35	0.68	0.66	0.67	0.59	0.69	0.68	0.81	0.82	0.80	0.45***(*2.80*)	0.54***(*2.94*)
REV	0.44	0.78	0.49	0.63	0.61	0.75	0.56	0.64	0.77	0.92	0.48***(*3.04*)	0.54***(*2.89*)
ILLIQ	0.48	0.59	0.62	0.78	0.77	0.69	0.71	0.88	0.81	0.87	0.39** (*2.30*)	0.45** (*2.22*)
IVOL	0.38	0.68	0.50	0.66	0.59	0.64	0.58	0.73	0.66	1.03	0.65***(*4.09*)	0.64***(*3.43*)
AG	0.54	0.60	0.60	0.65	0.64	0.59	0.60	0.89	0.82	0.95	0.40** (*2.54*)	0.41** (*2.18*)
OPR	0.47	0.52	0.65	0.69	0.62	0.64	0.64	0.73	0.86	0.93	0.46** (*2.38*)	0.63***(*2.93*)

Table C6: Fama-Macbeth Regression (Above-NYSE-Size-50th Sample)

This table presents the Fama-Macbeth (1973) regression results of month t+1 stock excess return r^i_{t+1} on $\beta^{spc}_{i,t}$ and control variables measured at the end of month t. The "ln(·)" denotes the natural log transformation. OPR* equals OPR if OPR is not missing and 0 otherwise. All independent variables are winsorized at the 0.5% and 99.5% levels every month. The t-statistics in parentheses are adjusted according to Newey and West (1987) with six lags. The sample period (month t) spans from December 1996 to December 2019, and the sample includes only those common stocks above the NYSE size 50th cutoff at the end of each month.

	Dependent variable: r^i_{t+1} in percentage			
	(1)	(2)	(3)	(4)
β^{spc}	7.379***	7.699***	7.400***	5.220***
	(2.77)	(3.17)	(3.24)	(2.95)
β^{capm}		-0.045	-0.018	-0.119
		(-0.12)	(-0.05)	(-0.38)
β^{vix}			0.965	-6.441
			(0.10)	(-0.77)
ln(BM)				0.001
				(0.02)
ln(SIZE)				-0.096*
				(-1.88)
MOM				0.148
				(0.47)
REV				-1.317*
				(-1.75)
ILLIQ				-22.179
				(-0.58)
IVOL				-9.343
				(-1.26)
AG				-0.280***
				(-3.58)
OPR*				0.747*
				(1.68)
Avg(adj. R^2)	0.6%	6.5%	7.0%	12.5%
Obs.	268,801	268,801	268,801	250,322