Slope Beta and Cross-Sectional Stock Returns

Abstract

We construct a slope measure (spc) by regressing at-the-money put-over-call implied volatility ratio on the maturity, and theoretically and empirically show that spc is negatively related to the discount rate. In the time-series, spc significantly and negatively predicts aggregate stock market return. In the cross-section, the exposure to spc (slope beta) negatively predicts stock returns, implying a positive price of discount rate risk. Stocks with low slope beta significantly outperform stocks with high slope beta by 0.51% (0.74%) per month under equal (value) weight, which is not explained by various factor models and robust to various stock characteristics as controls.

JEL classification: G12, G13

Keywords: Term structure of implied volatility spread, return predictability, time-series, cross-section, ICAPM.

1. Introduction

The price of discount rate risk is an important and contentious topic. To estimate the risk price, we first need a measure of the discount rate. The traditional VAR approach (vector autoregression) extracts this information from the future realized stock return[1], which equals the discount rate plus noise. As the signal-to-noise ratio is low, the results are typically in-sample, often insignificantly different from zero, and sensitive to the choice of predictors for the future return.

In this paper, we propose a new approach that utilizes information 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 each stock's covariance with the discount rate news using a short past rolling window rather than full-sample data. We then proceed with the standard asset pricing tests and find a significant and robust positive price of discount rate risk.

Specifically, our measure is constructed by regressing at-the-money put-over-call implied volatility ratio on the maturity, using S&P 500 index options[2]. We call this measure spc, as it represents the slope of this put-call ratio. Naturally, the primary driver of the option prices is the second moment of return. Our measure joins the recent effort to extract the information on the first moment of return from the option prices (e.g., Martin, 2017). By focusing on the ratio between two implied volatilities, we aim to isolate the effect of transitory volatility and thus capture the effect of expected return.

[1] See, e.g., Campbell (1991), Campbell (1996), Campbell and Vuolteenaho (2004), Bansal, Kiku, Shaliastovich, and Yaron (2014), and Campbell, Giglio, Polk, and Turley (2018).

[2] In the main specification, we use data for put at delta -0.5 and call at delta 0.5 because they are directly readable from the volatility surface. In the robustness test, we calculate spc from (interpolated) put and call implied volatility ratio at same strike price $K = S\exp(rT)$, and obtain similar results.

We quantitatively illustrate our point with the rare disaster model of Gabaix (2012), in which there is no in-sample disaster realization (so that there is no cash flow news) and the volatility is a constant (so that there is no volatility news). The spread between the implied volatilities of put and call is driven by the mean-reverting resilience to future disasters, which determines the discount rate. We show that spc is approximately linear in the resilience and hence the discount rate.

More generally, based on put-call parity, the price difference between a pair of at-the-money put option and call option equals the present value of dividends up to the maturity of the options, which is increasing in the maturity and decreasing in the level of the discount rate for dividends. Our slope measure, spc, becomes larger when the discount rate for dividend is lower, as the present value of the dividend per unit time increases. This argument holds both for models with exogenous variation in the discount rate, and for models with endogenous discount rate by the representative agent.[3] They share the same prediction in the time-series: spc should negatively predict future market return. However, they differ in the price of discount rate risk obtained from the cross-section of stocks since they disagree on whether the discount rate is high during good times (low marginal utility) or bad times (high marginal utility), as pointed out by Kozak and Santosh (2020). For the first type of models, a stock that positively co-varies with spc provides a hedge against deterioration of investment opportunity, and thus earns a lower expected return. For the second type of models, the same stock performs badly when the primitive bad shocks drive the discount rate to rise, and thus is considered risky and may earn a higher expected return.[4]

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[3] Models with exogenous variation include the ICAPM framework of, e.g., Campbell (1993), as well as behavioral models featuring one group of investors with erratic demand, e.g., Barberis, Greenwood, Jin, and Shleifer (2015).

[4] This prediction depends on the choice of parameter in the model. Kozak and Santosh (2020) clarify this issue in the context of the habit model and the long run risk model.

We start by verifying the predictability in the time-series. Indeed, we find that spc significantly and negatively predicts future stock market return at 6-months, 1-year, and 2-years horizons, and this relation is robust to a list of time-series predictors as controls. The economic magnitude is sizable (and comparable to the prediction from Gabaix (2012) model), with a one-standard-deviation increase of spc associated with 0.91%, 2.41%, and 3.46% decrease of next 6-months, 1-year, and 2-years market excess returns.

In the cross-section, we estimate individual stock's slope beta (β^{spc}) as its exposure to spc using past 12-months daily data and examine its relationship with future stock returns. We find a negative relation between the slope beta and future stock returns, in support of the positive price of discount rate risk[5]. The univariate portfolio analysis shows that portfolios sorted by β^{spc} can generate a monthly high-minus-low return spread about -0.51% (-0.74%) with t-statistics of -2.82 (-3.75) in the equal-weighted (value-weighted) case, which corresponds to -6.12% (-8.88%) annually. In addition, the alphas adjusted for a list of factor models, including CAPM, Fama-French three-factor and five-factor models, Carhart four-factor model, and the Q5 model in Hou, Mo, Xue, and Zhang (2021), still remain statistically significant and economically large. Furthermore, by tracking the return of β^{spc}-sorted short-long strategy over time, we find that the predictive ability of β^{spc} is not restricted to any specific period.

We also perform bivariate portfolio analysis and Fama-Macbeth regression with commonly used stock risks or characteristics as controls, including CAPM beta, volatility beta, size, book-to-market ratio, momentum, reversal, illiquidity, idiosyncratic volatility, asset growth, and profitability. The results suggest that the slope beta effect is not explained by these variables.

[5] Note that the price of discount rate risk is measured by examining the relation between stock's exposure to discount rate shocks and its future returns. Since our *spc* is negatively related to discount rate, the cross-sectional negative relation between slope beta and future stock returns actually implies a positive price for discount rate risk.

In the main analysis, we construct spc using put (call) implied volatility at delta -0.5 (0.5) in Volatility Surface for convenience. However, the theoretical analysis uses at-the-money options. Therefore, we estimate alternative spc from interpolation of put and call implied volatility at same strike $K = S\exp(rT)$. The results show that our findings are robust. We also conduct robustness tests for alternative slope betas (1) as exposure to spc innovations rather than exposure to spc, (2) with different factor returns as controls, or (3) after excluding some maturities in spc construction. The results are robust across these different specifications.

The results from the time series and the cross-section are consistent with the idea that spc contains information about the discount rate. However, it is also possible that the slope changes due to informed trading. For example, a strong demand to hedge future crash increases the implied volatility of long maturity put options, which could be the reason that spc negatively predicts future return. To distinguish between these two alternative explanations, we turn to individual stock options. Specifically, the informed trading argument would also apply to the options on individual stocks, whereas our discount rate hypothesis does not apply to individual stock options as the dividends of individual stock are discretely paid out. After constructing spc_i from individual stock options, we find that it does not provide additional information after controlling for other option-based predictors in the literature, while β^{spc} always exhibits significantly negative predictive ability, which helps us to rule out the informed trading explanation.

This paper is primarily a study of the price of discount rate risk. As pointed out by Chen and Zhao (2009), the traditional vector autoregressive approach that extracts discount rate news from realized return, such as Campbell and Vuolteenaho (2004), generate non-robust results. Recently, Kozak and Santosh (2020) estimate the covariance with discount rate directly and find a significantly negative risk price. However, their method requires a long time series of future realized return, uses full-sample information, and applies to portfolios. Our approach utilizes only historical data, applies to individual stocks, and thus corresponds to tradable strategies. We find a significant and positive risk price, consistent with the recent finding of Badidi, Boons, and Frehen (2022) who use the returns around macroeconomic announcement days.

Our work also contributes to the enormous research about option-implied information (See, e.g., the survey of Christoffersen, Jacobs, and Chang, 2013) and is particularly related to two strands of them. First, it complements the literature about put-call implied volatility spread by studying the term structure information. Cremers and Weinbaum (2010) document that the put-call implied volatility spread extracted from individual stock options predicts stock returns in the cross-section, and they explain it through the informed trading in option market. Bali and Hovakimian (2009) and Yan (2011) find similar evidence, but they attribute the predictive ability to its proxy for jump risk. Different from them, we focus on the term structure information and calculate spc from index option to examine it as both a time-series predictor and a systematic risk in the cross-section, rather than treating it as characteristics.

Second, this paper is also related to the literature about term structure of implied volatility. The term structure of implied volatility has been shown to predict future changes of short-term implied volatility (Mixon, 2007), cross-sectional option returns (Vasquez, 2017), and returns of variance-related assets (Johnson, 2017). However, to our knowledge, there seems to be no evidence that it can predict aggregate stock market return. In contrast, we study the term structure of put-over-call implied volatility spread and find that it is a good time-series predictor.

Related to our cross-sectional part, a working paper of Xie (2014) explores if term structure of implied volatility is a priced risk in the cross-section of stocks and finds that individual stock's exposure to changes of volatility term structure is related to its future return. However, the predictability seems to be limited, as the paper mainly focuses on the triple-sort and the high-minus-low return spread is small. This paper differs by looking at term structure of put-over-call implied volatility spread, and our slope beta is a much stronger return predictor in the cross-section.

2. spc and Aggregate Stock Market Return

2.1. Estimation of spc

We start by constructing spc to capture the term structure of put-over-call implied volatility ratio, which largely alleviates the influence of common volatility shocks. First, we define the put-call implied volatility ratio as[6]

$$PC_t^{(T)} = \frac{\sigma_{t,T}^{(-0.5put)}}{\sigma_{t,T}^{(0.5call)}} - 1$$

where $\sigma_{t,T}^{(-0.5put)}$ ($\sigma_{t,T}^{(0.5call)}$) is the date-t implied volatility of put (call) option with delta -0.5 (0.5) and maturity T for S&P 500 index option (secid=108105), which can be readily obtained from Volatility Surface in OptionMetrics. Here, we choose at-the-money option due to liquidity concern and our theoretical analysis below. In the robustness tests, we would try alternative definition of at-the-money option through strike price $K = S\exp(rT)$, instead of delta.

Next, for each day t, we run OLS regression of $PC_t^{(T)}$ on the corresponding maturity T using all available maturities in Volatility Surface (10, 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 days) to obtain the slope spc_t

$$PC_t^{(T)} = Intercept_t + spc_t \times \frac{T}{365} + \varepsilon_t$$

[6] Here, -1 does not affect the regression slope spc below.

The daily spc_t ranges from Jan 4, 1996 to Dec 31, 2019, a total of 6040 days. Figure 1 shows the time-series of spc_t at both daily and monthly frequency (month-end value)[7]. We can see that spc varies much over time, showing less persistence. This is confirmed in the summary statistics of Table 1. In particular, the mean of spc is much smaller than its standard deviation in magnitude, and spc sometimes can be quite high or low, with several standard deviations away from its mean. The first-order autocorrelation for spc is about 0.51 (0.33) at daily (monthly) frequency. The low persistence of spc seems to suggest that we can approximately treat the level of spc as shocks to spc, which we would utilize in the cross-sectional tests later.

[Insert Figure 1 here]

[Insert Table 1 here]

2.2. What does spc measure?

In this section, we show that spc is negatively related to the discount rate. We quantitatively assess this argument with a calibration of the Gabaix (2012) model, in which there is no in-sample disaster realization (so that there is no cash flow news) and the volatility is a constant (so that there is no volatility news). The dividend discount rate and the expected return on stock are one and the same thing in Gabaix (2012).[8] We use r_t to represent this discount rate, which is also the expected return on the stock.

Approximately, at-the-money option price is proportional to its implied volatility, i.e., $0.4 * \text{stock price} * \text{Volatility} * \text{sqrt}(\text{maturity})$. Hence, the put-call implied volatility ratio for at-the-money option is close to the at-the-money put-call option price ratio, i.e.,

[7] Although our focus is on the daily spc since we need to estimate individual stock's exposure to it using short rolling window in the cross-sectional test, we also use monthly spc in the time-series part for some purposes.

[8] In the model, the impact of a disaster varies over time. However, the level of dividend across different maturities is always affected equally. Therefore, the term structure of dividend discount rate is flat with a countercyclical level (see Appendix VII.B in Gabaix (2012)).

$$PC_t^{(T)} = \frac{\sigma_{t,T}^{(-0.5put)} - \sigma_{t,T}^{(0.5call)}}{\sigma_{t,T}^{(0.5call)}} \approx \frac{P_{t,T}^{ATM} - C_{t,T}^{ATM}}{C_{t,T}^{ATM}}$$

Therefore, spc approximately captures the slope of $\frac{P_{t,T}^{ATM} - C_{t,T}^{ATM}}{C_{t,T}^{ATM}}$ against the maturities. Via put-call parity for at-the-money options, the numerator measures the present value of dividends from time t to time T, which inversely depends on the discount rate of dividend. Hence,

$$\frac{P_{t,T}^{ATM} - C_{t,T}^{ATM}}{C_{t,T}^{ATM}} = \frac{\int_0^T e^{-r_t\tau} D_t d\tau}{C_{t,T}^{ATM}} = \frac{\int_0^T e^{-r_t\tau} q_t d\tau}{C_{t,T}^{ATM}/S_t},$$

where T is the maturity, D_t is the dividend level, and $q_t = D_t/S_t$ is the dividend yield. In Gabaix (2012), the dividend level D_t grows at a deterministic rate, which we simply set it to be 0 for illustration[9]. This is why, in the above formula, we discount the same D_t till the maturity of options. Using $\int_0^T e^{-r_t\tau} d\tau \approx \left(1 - \frac{r_t}{2}T\right)T$ from Taylor expansion and $C_{t,T}^{ATM}/S_t \approx 0.4\sqrt{T}\sigma_t$ from the approximate pricing formula for at-the-money option, we have

$$\frac{P_{t,T}^{ATM} - C_{t,T}^{ATM}}{C_{t,T}^{ATM}} \approx \frac{q_t}{0.4\sigma_t}\left(1 - \frac{r_t}{2}T\right)\sqrt{T}$$

The slope of this ratio against the maturity T is approximately

$$spc_t = \left.\frac{\partial \frac{P_{t,T}^{ATM} - C_{t,T}^{ATM}}{C_{t,T}^{ATM}}}{\partial T}\right|_{T=1} \approx \frac{q_t}{0.4\sigma_t}\left(\frac{1}{2} - \frac{3}{4}r_t\right)$$

which is evaluated at $T = 1$ as it is the average maturity of the observations in the data. It is straightforward to rewrite the formula as a predictive regression:

$$r_t = \frac{2}{3} - \frac{1.6\sigma_t}{3q_t} spc_t$$

[9] If we assume the dividend level D_t grows at a deterministic rate g_D rather than 0, then we can simply replace the r_t with $r_t - g_D$ in all the equations in this section. Finally, we would have $r_t = \frac{2}{3} + g_D - \frac{1.6\sigma_t}{3q_t} spc_t$.

In the specification of Gabaix (2012) (see Section III.C.), dividend yield q_t and volatility $\sigma_t = e^{\mu_{it}}\sigma$ (in Gabaix's Equation (22)) are both increasing functions of the expected return. However, the ratio of the two is essentially a constant with the calibration in the paper. Therefore, the above equation suggests that spc_t negatively predicts future stock return with the coefficient on spc_t being $-\frac{1.6\sigma_t}{3q_t} \approx -\frac{1.6*0.15}{3*0.05} = -1.6$, if we plug in $\sigma_t = 15\%$ and $q_t = 5\%$.

To conclude, spc is theoretically a (negative) proxy for the discount rate, which we verify in the empirical analysis below.

2.3. spc and aggregate stock market returns

We run the predictive regression of future h-days market excess return $R^M_{t,t+h}$ on spc_t

$$R^M_{t,t+h} = a + b \times spc_t + \varepsilon_t$$

where $R^M_{t,t+h}$ is calculated by compounding daily market excess returns from t+1 to t+h (both inclusively), and the horizon h can be 21, 63, 126, 252, or 504 trading days. The regression is run at daily frequency and the t-statistics are adjusted according to Newey and West (1987) with lags equal to the predictive horizon, i.e., 21, 63, 126, 252, or 504 lags. Here, we map 1 month calendar days with 21 trading days.

Table 2 shows the regression results. In the first five columns where we do not add any control variables, the coefficients on spc are negative across all predictive horizons, and they are significant at 6-months, 1-year, and 2-years horizons. As for the magnitude, a one-standard-deviation increase of spc is associated with a 0.91%, 2.41%, and 3.46% decrease of next 6-months, 1-year, and 2-years market excess returns (recall that the standard deviation of spc is 3.24% in Table 1), which are economically large.

For the horizons in which spc has a significant coefficient, we further control for the expected return bound in Martin (2017), which is a well-known predictor at daily frequency. The results are shown in the last three columns. We can see that the coefficients on spc are still significantly negative, which implies that spc carries additional information with respect to the return bound. For the return bound, the coefficients are all close to 1, consistent with Martin (2017), and they are significant at 6-months and 1-year horizons, although weaker at 2-years horizon.

[Insert Table 2 here]

To include more time-series predictors (mostly at monthly frequency) as controls, we need to perform the predictive regression at monthly frequency. First, we check if the predictive ability of spc still exists at monthly frequency. Panel A of Table 3 shows the regression results of next h-months market excess return $R^M_{s,s+h}$ on spc_s at the end of month s. The horizon h can be 1, 3, 6, 12, or 24 months, and $R^M_{s,s+h}$ is calculated by compounding monthly market excess returns from month s+1 to s+h (both inclusively). The t-statistics are adjusted according to Newey and West (1987) with lags equal to the predictive horizon, i.e., 1, 3, 6, 12, or 24 lags. We can see that the coefficients on spc are all negative and they are significant at 1-year and 2-years horizons, broadly consistent with Table 2.

Second, to examine if spc can provide additional information for return prediction, we add other popular time-series predictors, which include the comprehensive time-series predictors in Goyal and Welch (2008) from Amit Goyal's website[10], the variance risk premium in Bollerslev, Tauchen, and Zhou (2009) with the realized variance part from lag or statistical forecast (denoted

[10] The predictors in Goyal and Welch (2008) include the log of dividend to price ratio (dp), log of dividend to lagged price ratio (dy), log of earnings to price ratio (ep), log of dividends to earnings 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 value to market value 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 which is the difference between the long-term yield on government bonds and the Treasury-bill (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), and the Consumer Price Index (infl).

by vrp and evrp), which are obtained from Hao Zhou's website, and the expected return bound in Martin (2017) at each month-end (rbound). Here, we focus on 1-year horizon. Panel B (except the "All Sig." column) of Table 3 shows the results when adding these predictors as control one by one. As is shown, the coefficient on spc is always significantly negative no matter which predictor is added as control.

Finally, notwithstanding the multicollinearity issue, in the "All Sig." column of Panel B, we simultaneously control for dy, de, svar, bm, tbl, tms, dfy, infl, vrp, and rbound, which are significant in the bivariate regression with spc.[11] The coefficient on spc remains significantly negative with all these variables as controls.

[Insert Table 3 here]

Notice that the point estimates of regression slope for the 1-year horizon, i.e., -0.745 in Table 2 and -1.113 in Table 3, are comparable to the theoretical prediction of -1.6 in Section 2.2, but the regression intercept differs much. Therefore, an out-of-sample analysis which takes the coefficients from the model will not generate a good out-of-sample R^2. This is reasonable since our theoretical analysis involves simplified assumptions and we only use it to reveal the negative relation between spc and expected return. In unreported test, we also examine the out-of-sample performance using traditional rolling or expanding window regression, though fail to obtain good results. However, this does not necessarily mean spc is useless, especially when considering the unstable parameter estimates in traditional out-of-sample approach (Goyal and Welch, 2008). Since spc is only available from 1996, the short sample period is hard for us to balance between obtaining reliable parameter estimates from as long initial sample as possible

[11] We exclude dp since it is highly correlated with dy (about 0.98) and dy has a higher t-statistics than dp in the bivariate regression with spc. Nonetheless, including dp does not affect the significant level of spc.

and evaluating out-of-sample performance through enough evaluation sample. We would like to reexamine the out-of-sample performance when more data becomes available.

3. Slope Beta and Cross-Sectional Stock Returns

The time-series regression results validate our conjecture that spc carries information about the discount rate, which makes it a potential state variable for future investment opportunities (Campbell, 1993; Maio and Santa-Clara, 2012). According to ICAPM, shocks to spc should be priced in the cross-section, which we test in this section.

3.1. Slope Beta

Individual stock's slope beta (β^{spc}) is defined as its exposure to market spc shocks. However, as is shown in Section 2.1, spc varies much over time and is not very persistent. Hence, we directly use the level of spc to represent shocks to spc.[12] Specifically, at the end of each month, for each stock, β^{spc} is estimated by regressing its daily excess return on the daily spc while controlling for some common factors

$$R_{i,s} = a_i + \beta_i^{spc} spc_s + \beta_i^{m} MKT_s + \beta_i^{smb} SMB_s + \beta_i^{hml} HML_s + \beta_i^{umd} UMD_s + \varepsilon_{i,s}$$

where $R_{i,s}$ is the excess return (over risk free rate) of stock i at day s. MKT_s, SMB_s, HML_s, and UMD_s are the contemporaneous daily factor returns of Carhart four-factor model. In the robustness tests, we also consider alternative factor returns as control. The regression is run at the end of each month using past 12-month daily data, requiring at least 200 valid observations. The daily stock return data is obtained from CRSP. Since the daily spc starts from Jan 4th 1996, the data for β^{spc} is available from the end of Dec 1996.

[12] In the robustness tests, we use AR(1) model to extract the spc innovations and estimate β^{spc} accordingly.

3.2. Sample and Controls

In the cross-sectional analysis, the monthly stock return and characteristics that we use are mainly obtained from the open source asset pricing dataset provided by Chen and Zimmermann (2021), which is described in detail in the Internet Appendix A. We restrict the sample to be all US common stocks listed in NYSE, NASDAQ, and AMEX. In addition, to mitigate the influence of micro-cap stocks, we focus on those stocks with market capitalization above NYSE size 20th cut-off at the end of each month, where the NYSE size breakpoint data is from Kenneth French's website.[13]

To examine if β^{spc} contains some distinct information for return prediction, we add a list of commonly used 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 in millions of dollars (SIZE), book-to-market ratio (BM) in Fama and French (1992), momentum (MOM) in Jegadeesh and Titman (1993), 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)[14]. Most of these control variables are obtained from the open source asset pricing dataset with some small modifications. Internet Appendix B provides the detailed descriptions.

Our final sample contains monthly β^{spc} and other stock characteristics from Dec 1996 to Dec 2019 and the one month-ahead stock return data from Jan 1997 to Jan 2020, a total of 277 months. For our purpose, we keep only those stock-month observations with valid β^{spc} and

[13] In the Internet Appendix C, we also repeat the main cross-sectional analysis using the all-stocks sample that does not restrict market capitalization and the large-cap sample that requires stocks to have market capitalization above NYSE size 50th cut-off at the end of each month. The results are still significant and the conclusions do not change.

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

one-month-ahead stock return. Table 4 shows the summary statistics, with the time-series averages of cross-sectional statistics and correlation matrix in Panel A and B respectively. For the main sample (above-NYSE-size-20th), we have on average 1919 stocks with valid β^{spc} each month and the average cross-sectional mean of market capitalization is around 8.6 billion dollars.

From Panel A of Table 4, 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} and serve as hedging assets for deterioration of future investment opportunities under the ICAPM context. Panel B shows that β^{spc} has very mild correlation with other stock characteristics, suggesting that β^{spc} captures distinct information from them.

[Insert Table 4 here]

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 returns. At the end of each month t, stocks are sorted into 10 groups based on ascending order of β^{spc}. Then, for each portfolio, we calculate its equal-weighted and value-weighted excess returns in month t+1. Table 5 shows 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 by a long list of factor models. 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). The t-statistics are adjusted according to Newey and West (1987) with 6 lags, which is approximately equal to $4 * (\mathrm{T}/100)^{2/9}$, as suggested in Bali, Engle, and Murray (2016).

From Table 5, we can see a clear negative relation between β^{spc} and one-month-ahead portfolio excess returns. Panel A shows that in the equal-weighted case, the average portfolio excess return drops almost monotonically from 0.95% to 0.43% as β^{spc} increases, yielding a high-minus-low return about -0.51% per month (t-statistics of -2.82). This corresponds to a simple annualized return around -6.12%, which is sizable. In addition, the alphas of high-minus-low return with respect to different factor models are close to the raw return, and they are all statistically significant. The value-weighted results in Panel B are even stronger, with high-minus-low return and alphas ranging from -0.66% to -0.74% per month (or -7.92% to -8.88% annually) and t-statistics almost all above 3.

[Insert Table 5 here]

Table 6 reports the factor loadings of the high-minus-low returns on different factors. As is shown, the loadings are never significantly negative, but significantly positive on momentum factor (the equal-weighted case) and value or investment factor[15] (the value-weighted case), which actually amplify the magnitude of alphas. In addition, the adjusted R squares remain low across different factor models. These suggest that factor models explain little about the return spread sorted by β^{spc}.

[Insert Table 6 here]

To examine if the predictive ability of β^{spc} for next-month stock return is stable over time, we plot in Figure 2 the cumulative sum of monthly *low-minus-high* return spread sorted by β^{spc}, with equal-weighted (value-weighted) case on the left (right) panel. Both panels show a clearly upward trend, albeit more evident for the value-weighted case. We therefore conclude that the predictive ability of β^{spc} is not restricted to any specific periods.

[15] Note that the HML in Fama-French models and R_IA in Q5 model are related due to the investment-q relation.

[Insert Figure 2 here]

Table C1 and C4 in the Internet Appendix C present the results of univariate portfolio analysis for the all-stocks sample and above-NYSE-size-50th sample. As one might expect, the magnitude and t-stats for the high-minus-low return and alphas are higher in all-stocks sample and lower in above-NYSE-size-50th sample. Nonetheless, they are all significantly negative. Especially for the above-NYSE-size-50th sample that consists of large cap and liquid stocks, the significant result further confirms the predictive ability of β^{spc}.

3.4. Average Characteristics

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 each month t, for each stock characteristic, we calculate its month-t equal-weighted average value across stocks within each β^{spc}-sorted portfolio. The time-series averages of each portfolio's characteristics and the average difference between high-β^{spc} and low-β^{spc} portfolios are shown in Table 7.

We can see that, in addition to β^{spc}, which increases monotonically by construction, only momentum and profitability exhibit significant difference between high-β^{spc} and low-β^{spc} portfolios, although the patterns are not that monotone. This is consistent with Table 4 that β^{spc} has relatively low correlation (in magnitude) with other stock characteristics. High-β^{spc} portfolio seems to have lower profitability and experience lower returns in the past, compared with low-β^{spc} portfolio. 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 in the bivariate portfolio analysis and Fama-Macbeth regression, this is not the case.

[Insert Table 7 here]

3.5. Bivariate Portfolio Analysis

We now perform bivariate portfolio analysis to formally test if the predictive ability of β^{spc} for future stock return can be explained by other stock characteristics one by one. Specifically, at the end of each month t, stocks are first sorted into 10 groups based on the control variables one at a time, and then within each control group, stocks are further sorted into 10 groups based on 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. For each β^{spc} group, its month t+1 excess return is the average month t+1 excess return across 10 control groups.

Table 8 shows the time-series average of month t+1 excess return for each β^{spc} group, as well as the high-minus-low portfolio, after accounting for the effect of control variables one at a time. For the high-minus-low portfolio, we only report its raw return and six-factor alpha for brevity, but the alphas adjusted for other factor models are all significant as well. From Table 8, we can see that both the high-minus-low return spread and its six-factor alpha remain significantly negative no matter which control variable we control for or which kind of weighting method is used. This suggests that the negative relation between β^{spc} and future stock returns cannot be explained by any one of these control variables.

[Insert Table 8 here]

Table C2 and C5 in the Internet Appendix C report the results of bivariate portfolio analysis for the all-stocks sample and above-NYSE-size-50th sample. In both samples, the high-minus-low return and its six-factor alpha are all significantly negative across different control variables and weighting methods, which strengthens the conclusion that β^{slope} contains some distinct information from other stock characteristics.

3.6. Fama-Macbeth Regression

To control for multiple control variables simultaneously, we run Fama and Macbeth (1973) regression of month t+1 stock excess return on the β^{spc} and control variables at the end of month t. The results are shown in Table 9. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags.

In specification 1 where we do not add any control variables, the coefficient on β^{spc} is significantly negative, with a t-statistics of -3.23. As for the magnitude, a one-standard-deviation increase of β^{spc} is associated with a 0.18% drop of next-month return (-2.99%*0.061, where 0.061 is the average cross-sectional standard deviation of β^{slope} in Table 4), or 2.16% annually. In specification 2, we further control for the CAPM beta. The magnitude and significance level of the coefficient on β^{spc} remain largely unchanged, suggesting that β^{spc} contains distinct information from CAPM beta. Meanwhile, the coefficient on CAPM beta is slightly negative and insignificant, consistent with literature about flat SML (e.g., Fama and French, 1992). In specification 3, we further control for the volatility beta in Ang, Hodrick, Xing, and Zhang (2006), which measures stock's sensitivity to changes in expected volatility (also related to changes in future investment opportunities). Again, the coefficient on β^{spc} does not change much and is still quite significant, implying that β^{vix} also cannot explain the predictive ability of β^{spc}. This is expected since we use implied volatility ratio in spc construction to mitigate the influence of common volatility shocks. The coefficient on β^{vix} is positive, inconsistent with Ang, Hodrick, Xing, and Zhang (2006), but it is insignificant. This may be due to the different stock samples and time periods we use.

In specification 4, we further control for some 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 still remains significant at 1% level. This indicates that β^{spc} contains some distinct information from these characteristics.[16]

[Insert Table 9 here]

Table C3 and C6 in the Internet Appendix C show that the coefficients on β^{spc} are significantly negative across all the regression specifications under both the all-stocks sample and above-NYSE-size-50th sample. In particular, the significant negative coefficients on β^{spc} at 1% level for the above-NYSE-size-50th sample give us more confidence about the predictive ability of β^{spc}.

3.7. Longer Horizons

As a further test, we examine if the predictive ability of β^{spc} goes beyond the one month horizon. To do this, we perform Fama-Macbeth regression of next h-months stock excess returns $R^i_{t\to t+h}$ on β^{spc} at the end of month t, under the four different regression specifications in Table 9. The $R^i_{t\to t+h}$ is calculated by compounding monthly stock returns from month t+1 to month t+h (both inclusively) and then minus the corresponding risk-free rate. Here, the horizon h can be 3, 6, 9, or 12 months.

The results are summarized in Table 10. We see that the regression coefficients on β^{spc} are significantly negative across different regression specifications under the 3-months and 6-months

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16 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. This may result from the larger and more liquid stocks we use and different time periods from prior literature. In fact, for the all-stocks sample in Table C3 of the Internet Appendix C, the control variables have generally significant coefficients with correct signs.

horizons. For the 9-months and 12-months horizons, β^{spc} still shows some predictive ability, although not always significant.

[Insert Table 10 here]

4. Robustness

4.1. Alternative spc

Previously, we calculate spc as the slope of the implied volatility ratio of put (delta -0.5) over call (delta 0.5), which can be easily mapped to Volatility Surface data. However, the strike prices at delta -0.5 and 0.5 are different and the slope cannot be directly mapped to the theoretical prediction in Section 2.2. Therefore, for robustness, we use at-the-money options with strike price at $K = S\exp(rT)$, where K, S, r, and T represent strike price, stock price, risk-free rate, and maturity. The risk-free rates at different maturities are obtained from linear interpolation of zero-coupon yield curve in OptionMetrics.

To calculate the alternative spc, we first interpolate to obtain the put and call implied volatility at strike $K = S\exp(rT)$ through natural cubic spline. The data we use to interpolate is either from Volatility Surface (implied volatility and implied strike at regular maturities) or from option trading data in OptionMetrics[17] (implied volatility and strike price at irregular maturities). After obtaining the interpolated put and call implied volatility, we calculate the put-call implied volatility ratio and the slope of it against maturity as new spc. These two alternative slopes are denoted by spc^{interp_VS} and spc^{interp_TR}, respectively.

[17] We filter the option trading data from OptionMetrics ("opprcd" file) as follows: (1) the implied volatility field is required to not be missing; (2) the maturity should be at least 10 days; (3) the best bid price should be larger than 0; (4) if there are duplicate records with same date, maturity, strike price, and cp_flag, then just keep the one with largest volume or open interest.

Table 11 shows the time-series predictive regression results for these alternative spc. We focus on the 1-year predictive horizon (the dependent variable is $R^M_{t,t+252}$ in Table 2, or $R^M_{s,s+12}$ in Table 3). For the $R^M_{s,s+12}$ case, we only present the regression results without control and with "All Sig." control in Table 3 for brevity, but the coefficients on new spc with control variables one by one in Panel B of Table 3 are all significant. From Table 11, we can see that the coefficients for both spc^{interp_VS} and spc^{interp_TR} are significantly negative across specifications, consistent with the results in Table 2 and 3.

Next, we reexamine the cross-sectional results by estimating slope beta as stock's exposure to these new spc, denoted by $\beta^{spc}_{interp\_VS}$ and $\beta^{spc}_{interp\_TR}$, respectively. Table 12 summarizes the main cross-sectional results for alternative slope betas, with high-minus-low return spread of univariate sort and its six-factor alpha in Panel A, and the Fama-Macbeth regression coefficients on slope beta in Panel B. From the first two columns, we can see that both slope betas generate significantly negative high-minus-low return spreads and Fama-Macbeth regression coefficients. Overall, the results suggest that our findings are not driven by the definition of at-the-money option.

4.2. Exposure to spc Innovations

In Section 3, we directly estimate slope beta as individual stock's exposure to market spc by observing the fact that spc is not very persistent. Here, for robustness, we rely on AR(1) model to first extract spc innovations and then estimate slope beta as stock's exposure to them.

Using the full sample to estimate spc innovations is more accurate. However, this is not feasible for real-time investors. Therefore, we also consider using only available information till the end of each month: rolling past 12-month data or all available data until current month end (with at least 12 months). We choose 12-month window to match the estimation window of slope beta. After obtaining the spc innovations, the new slope beta is estimated in the same way as Section 3.1 except that spc is now replaced by spc innovations over the past 12 months. These alternative slope betas are denoted by $\beta^{spc}_{Full\_AR}$, $\beta^{spc}_{Roll\_AR}$, and $\beta^{spc}_{Expand\_AR}$, respectively.

From the 3rd to 5th column in Table 12, we can see that the new slope betas from spc innovations still yield significantly negative high-minus-low return spreads and Fama-Macbeth regression coefficients. However, by comparing the magnitude and significance level with the results of original slope beta in Section 3, we notice that the predictive ability for these three new slope betas is weaker. This is possibly because spc is not persistent and therefore it is hard to estimate its conditional expectations and innovations accurately.

4.3. Different Factor Controls

We now test if estimating slope beta with different combinations of factor returns as controls would affect the results much. The new β^{slope} is now estimated via

$$R_{i,t} = a_i + \beta_i^{slope} spc_t + \sum_j \beta_i^j F_{j,t} + \varepsilon_{i,t}$$

where $F_{j,t}$ is the daily factor return for factor j at day t. In Section 3, we choose F to be Carhart (1997) four factors, while now it can be 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.

The 6th to 10th columns in Table 12 show the main cross-sectional results for these alternative slope betas. We can see that the high-minus-low return spreads and alphas are all negative and almost always significant. For the Fama-Macbeth regression coefficients on slope beta, they are all significantly negative across different regression specifications. These results are broadly consistent with those of the original slope beta.

4.4. Maturity Selection

So far, we use all available maturities in Volatility Surface to construct spc and estimate slope beta accordingly. For robustness, we now examine if excluding some maturities in spc construction would make any large difference. Two variants are tested. The first is to exclude the 10-days maturity since it is not available before Nov 2005. The second is to exclude maturities above 1 year due to liquidity concern. After obtaining these new spc, the new slope betas (β_{ex10}^{spc} and $\beta_{ex\geq 1Y}^{spc}$) are estimated in the same way as Section 3.1.

The last two columns in Table 12 show that our results are robust to these alternative slope betas[18], with significantly negative high-minus-low return spreads and alphas and the Fama-Macbeth regression coefficients.

[Insert Table 11 here]

[Insert Table 12 here]

4.5. spc from Individual Stock Option

We propose that spc captures information about discount rate. Alternatively, spc might be related to investors' relatively pessimistic view about the long term, such as slowly unfolding crisis. By definition, spc is high when long maturity put options become expensive, which could be the result of informed trading in the option market (Easley, O'Hara, and Srinivas, 1998). This hypothesis also implies that spc negatively predicts future stock market return, and that stocks which positively co-vary with spc provide hedges against slowly unfolding crisis.

We take this hypothesis to the individual stock options, where the presence of informed investors is likely far more prevalent than in the index options market. On the other hand, our theoretical analysis about spc in Section 2.2 requires continuous dividend paying and involves

[18] Here, we only report the cross-sectional results, but the time-series results for these two alternative spc are quite similar to those in Section 2.

put-call parity which is often violated for individual stock options that are American style, face more stringent short sell constraints, etc. (e.g., Ofek, Richardson, and Whitelaw, 2004). Hence, we are able to distinguish between these two alternative hypothesis by exploring whether the spc extracted from individual stock options can negatively predicts future individual stock return. To this end, we calculate spc_i at individual stock level following the same procedure in Section 2.1. This further restricts our above-NYSE-size-20th sample to those stocks with options. We also require individual stock options to have valid $PC_t^{(T)}$ for at least 10 maturities in Volatility Surface (11 maturities in total) because the spc_i calculated from too few maturities is likely to be more extreme. We keep only the month-end spc_i and use the CRSP-OptionMetrics linkage provided by WRDS to link datasets.

We examine the pricing of spc_i in the cross-sectional stock returns through Fama-Macbeth regression in Table 13. In the first four columns, we regress month t+1 stock excess return on spc_i at the end of month t, under the four kinds of control variable combinations in Table 9. The coefficient on spc_i is significantly positive, contrary to the informed trading hypothesis. Since we now focus on those stocks with options, we need to control for other option-based predictors to see if spc_i provides additional information. In column 5, we further control for the implied volatility skew of Xing, Zhang, and Zhao (2010), implied volatility spread of Yan (2011), and risk-neutral skewness of Stilger, Kostakis, and Poon (2017)[19], denoted by IVSKEW, IVSPREAD, and RNS. The coefficient on spc_i becomes negative, but not significant. In contrast, the coefficients on IVSKEW, IVSPREAD, and RNS are all significant and the signs are consistent with prior literature. This suggests that the significant positive coefficients on spc_i in the first

[19] We follow Yan (2011) to construct IVSKEW and IVSPREAD directly from Volatility Surface data. Specifically, the implied volatility spread is the implied volatility difference between put (delta=-0.5) and call (delta=0.5) with 30 days maturity, and the implied volatility skew is the implied volatility difference between put (delta=-0.1) and call (delta=0.5) with 30 days maturity. Similarly, RNS is also constructed using the 30-days maturity data from Volatility Surface, following the formulas in Bakshi, Kapadia, and Madan (2003).

four columns are due to its correlation with the three option-based predictors and spc_i itself does not contain additional information.

In the next five columns, we include both spc_i and β^{spc}, with the same sets of control variables as the first five columns. Similarly, the coefficient on spc_i changes from significantly positive to insignificantly negative when the three option-based predictors are added as controls. On the contrary, the coefficient on β^{spc} is always significantly negative across different regression specifications. Therefore, the result does not support the informed trading hypothesis, but in favor of our initial argument.

[Insert Table 13 here]

5. Conclusions

In this paper, we explore the information content in term structure of implied volatility spread. We compute at-the-money put-over-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 show that spc captures information about the discount rate, with high spc associating with low expected return, which we verify empirically in the time-series predictive regression.

In the cross-section, by treating spc as a state variable for future investment opportunities in ICAPM, we show that stocks' exposure to market spc (slope beta, or β^{spc}) negatively predicts their future returns. Low-β^{spc} stocks significantly outperform high-β^{spc} stocks by 0.51% (0.74%) per month under equal (value) weight, which is robust to various controls and specifications. The result suggests that the price of discount rate risk is positive.

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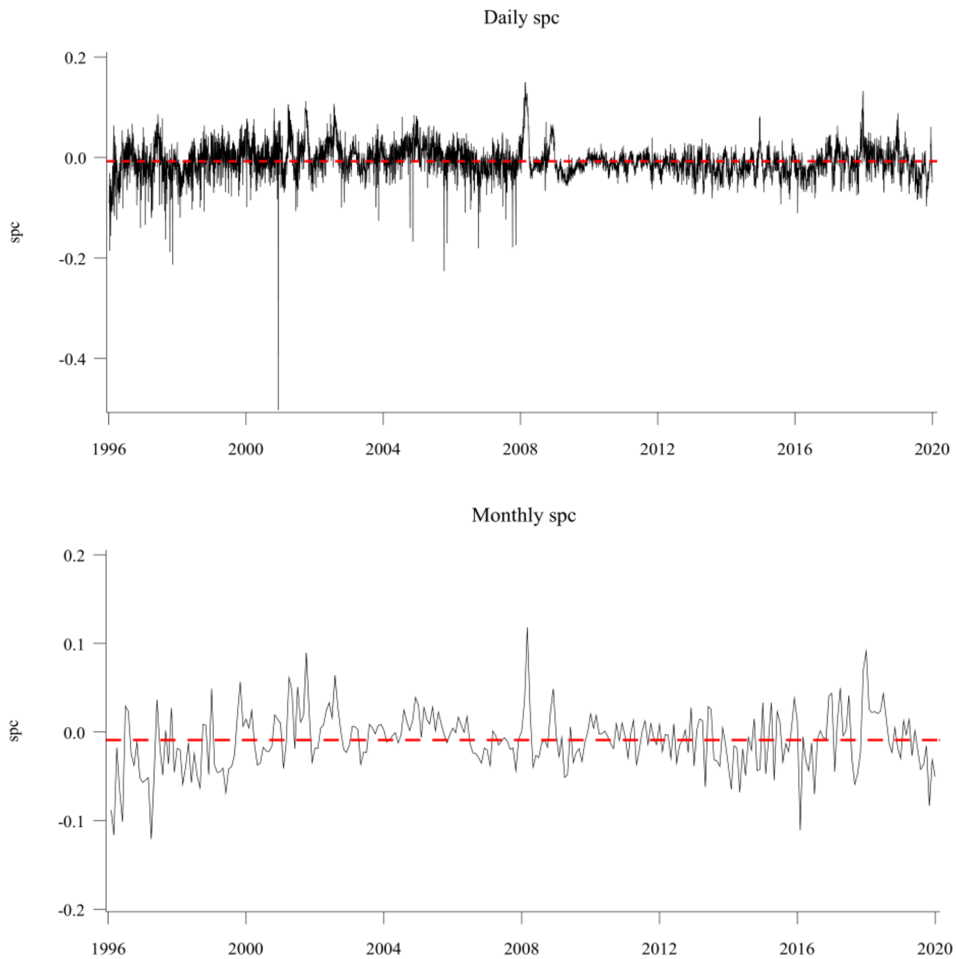

Figure 1: Time-series of spc. The top and bottom panels refer to the daily and monthly spc (month-end value), respectively, with the red dashed line as the sample mean. The data ranges from Jan 1996 to Dec 2019.

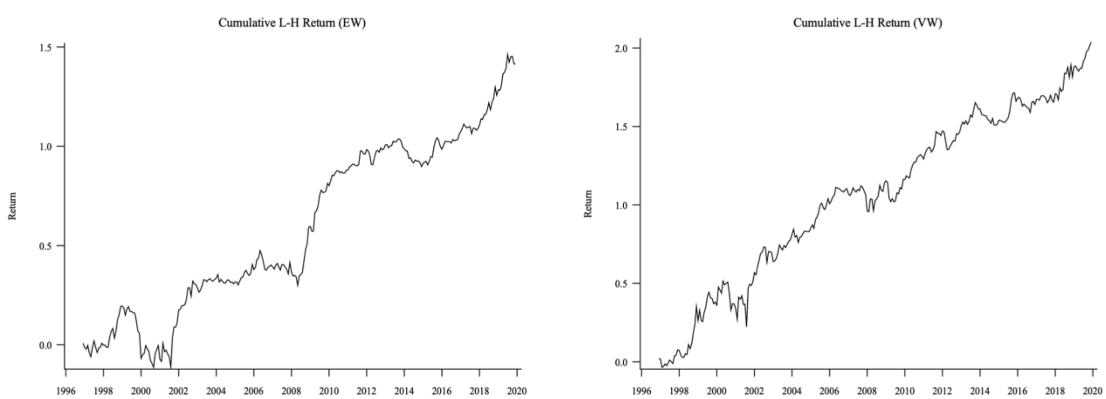

Figure 2: Cumulative Sum of β^{spc}-sorted Low-minus-high Return. The left and right panels show the equal-weighted and value-weighted results, respectively.

Table 1: Summary Statistics for spc

This table shows the summary statistics for daily and monthly spc. The monthly spc is the month-end value of daily spc. In the last column, we also present the first-order autocorrelation coefficient. The data ranges from Jan 1996 to Dec 2019.

	Mean	Std.	Min	P25	P50	P75	Max	Skew	N	AR1
Daily $spc \times 100$	-0.74	3.24	-50.25	-2.52	-0.87	0.95	14.97	-0.55	6040	0.51
Monthly $spc \times 100$	-0.90	3.24	-12.04	-2.88	-0.89	1.01	11.81	-0.02	288	0.33

Table 2: spc and Future Stock Market Return (Daily Frequency)

This table shows the predictive regression of future stock market excess return with different horizons $R^M_{t,t+h}$ on spc_t. The regression is run at daily frequency. $R^M_{t,t+h}$ represents the h-days market excess returns by compounding daily market excess returns from t+1 to t+h (both inclusively). The horizon h can be 21, 63, 126, 252, or 504 trading days. In the last three columns, the RBound at daily frequency, which is the lower bound of expected market excess return for different horizons (Martin, 2017), is added as control. The Newey and West (1987) t-statistics with lags equal to the predictive horizon are reported in parenthesis. The date t ranges from Jan 4th 1996 to Dec 31th 2019.

	$R^M_{t,t+21}$	$R^M_{t,t+63}$	$R^M_{t,t+126}$	$R^M_{t,t+252}$	$R^M_{t,t+504}$	$R^M_{t,t+126}$	$R^M_{t,t+252}$	$R^M_{t,t+504}$
Const.	0.007***	0.019***	0.037***	0.077***	0.172***	-0.012	0.001	0.066
	(2.93)	(2.80)	(2.77)	(2.70)	(2.98)	(-0.64)	(0.02)	(0.61)
spc_t	-0.008	-0.115	-0.280*	-0.745***	-1.068***	-0.366**	-0.827***	-1.183***
	(-0.16)	(-1.14)	(-1.92)	(-2.72)	(-2.64)	(-2.40)	(-2.88)	(-3.04)
RBound						2.350***	1.889**	1.366
						(2.91)	(2.28)	(1.24)
Adj. R^2	-0.01%	0.20%	0.60%	1.98%	1.64%	6.80%	7.18%	5.08%
N	6040	6040	6040	6040	6040	6040	6040	6040

Table 3: spc and Future Stock Market Return (Monthly Frequency)

Panel A shows the predictive regression of future stock market excess return at different horizons $R^M_{s,s+h}$ on spc_s at the end of each month. The regression is run at monthly frequency. $R^M_{s,s+h}$ represents the h-months market excess returns by compounding monthly market excess returns from month s+1 to month s+h (both inclusively). The horizon h can be 1, 3, 6, 12, or 24 months. Panel B (except the "All Sig." column) presents the regression results of $R^M_{s,s+12}$ on spc_s, with other popular time-series predictors as control one by one (the column name is the control variable). In the "All Sig." column, we simultaneously control for dy, de, svar, bm, tbl, tms, dfy, infl, vrp, and rbound, which are significant in the bivariate regression with spc. We exclude dp since it is highly correlated with dy (about 0.98) and dy has a higher t-statistics than dp in the bivariate regression with spc. In both panels, the Newey and West (1987) t-statistics with lags equal to the predictive horizon are reported in parenthesis (4 lags for the "cay" column of Panel B since it is at quarterly frequency). The month s ranges from Jan 1996 to Dec 2019.

Panel A: Predictive regression without control variables

	$R^M_{s,s+1}$	$R^M_{s,s+3}$	$R^M_{s,s+6}$	$R^M_{s,s+12}$	$R^M_{s,s+24}$
Const.	0.006**	0.017**	0.035**	0.072**	0.168***
	(2.34)	(2.35)	(2.57)	(2.49)	(2.87)
spc_s	-0.017	-0.168	-0.325	-1.113***	-1.286**
	(-0.26)	(-1.11)	(-1.52)	(-3.90)	(-2.43)
Adj. R^2	-0.33%	0.12%	0.51%	4.22%	2.07%
N	288	288	288	288	288

Panel B: Predictive regression with control variables in the column name (dependent variable is $R^M_{s,s+12}$)

	dp	dy	ep	de	svar	csp	bm	ntis	tbl	lty
Const.	1.721***	1.732***	0.130	0.142***	0.060**	-0.030	-0.200**	0.073**	0.128***	0.188***
	(4.07)	(4.50)	(0.49)	(3.58)	(2.10)	(-0.37)	(-2.14)	(2.57)	(4.61)	(2.85)
spc_s	-0.927***	-0.847**	-1.114***	-1.074***	-1.177***	-1.923***	-1.186***	-1.012***	-1.324***	-1.200***
	(-2.83)	(-2.53)	(-3.94)	(-3.49)	(-3.87)	(-5.23)	(-3.91)	(-3.49)	(-4.48)	(-4.01)
Control	0.411***	0.414***	0.018	0.081**	3.693*	-37.127	1.016***	1.430	-2.679**	-2.690
	(3.94)	(4.33)	(0.21)	(2.15)	(1.69)	(-1.05)	(3.33)	(0.87)	(-2.15)	(-1.56)
Adj.R^2	27.84%	28.07%	4.04%	7.89%	5.04%	13.49%	21.57%	6.46%	14.08%	9.39%
N	288	288	288	288	288	84	288	288	288	288

	ltr	tms	dfy	dfr	infl	cay	vrp	evrp	rbound	All Sig.
Const.	0.071**	0.007	-0.009	0.072**	0.087***	0.076***	0.057**	0.060**	0.003	1.727**
	(2.45)	(0.14)	(-0.18)	(2.51)	(3.40)	(2.87)	(2.05)	(2.16)	(0.07)	(2.28)
spc_s	-1.114***	-1.249***	-1.172***	-1.103***	-1.165***	-1.655***	-1.065***	-1.129***	-1.147***	-0.698**
	(-3.85)	(-4.31)	(-3.93)	(-3.94)	(-3.88)	(-3.99)	(-3.59)	(-3.86)	(-3.70)	(-2.06)
Control	0.176	2.931*	8.128*	0.607	-8.981**	-0.295	0.096*	0.068	1.708**	-----
	(0.63)	(1.80)	(1.96)	(1.03)	(-2.39)	(-0.35)	(1.70)	(1.52)	(2.12)	-----
Adj.R^2	3.98%	9.04%	7.83%	4.28%	7.32%	7.11%	5.38%	4.67%	8.23%	41.88%
N	288	288	288	288	288	96	288	288	288	288

Table 4: Summary Statistics

This table shows the summary statistics for the cross-sectional variables, including slope beta (β^{spc}), CAPM beta (β^{capm}), volatility beta (β^{vix}), book-to-market ratio (BM), market capitalization in millions 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 while Panel B shows the time-series average of cross-sectional correlation matrix, with the lower (upper) triangle referring to the Pearson (Spearman) correlation coefficient. The data ranges from Dec 1996 to Dec 2019, and includes only those common stocks that have valid β^{spc} and are above NYSE size 20th cut-off 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}	-0.001	0.061	-0.411	-0.096	-0.032	0.000	0.032	0.093	0.420	0.09	1919
β^{capm}	1.081	0.465	-0.204	0.446	0.757	1.010	1.337	1.957	3.247	0.75	1919
β^{vix}	0.001	0.009	-0.065	-0.012	-0.004	0.000	0.005	0.014	0.071	0.15	1919
BM	0.543	0.443	0.003	0.105	0.268	0.451	0.709	1.235	6.739	3.86	1738
SIZE	8566.8	26824.2	496.9	563.0	950.1	1966.7	5419.3	33144.3	481753.0	8.97	1919
MOM	0.211	0.571	-0.784	-0.349	-0.069	0.117	0.350	1.036	9.247	5.06	1906
REV	0.018	0.119	-0.473	-0.143	-0.043	0.011	0.069	0.197	1.398	2.10	1919
ILLIQ	0.020	0.282	0.000	0.000	0.001	0.003	0.009	0.051	10.862	27.30	1906
IVOL	0.018	0.012	0.001	0.007	0.011	0.015	0.022	0.038	0.183	4.45	1919
AG	0.202	0.738	-0.745	-0.130	0.005	0.081	0.209	0.834	19.567	13.61	1786
OPR	0.171	0.123	-0.964	0.018	0.111	0.162	0.225	0.358	0.969	-0.59	1360

Panel B: Average cross-sectional correlation

	β^{spc}	β^{capm}	β^{vix}	BM	SIZE	MOM	REV	ILLIQ	IVOL	AG	OPR
β^{spc}		-0.019	-0.003	0.002	-0.007	-0.046	-0.020	-0.008	0.010	-0.013	-0.022
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	0.000	-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	-0.020	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	0.168	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	-0.021	-0.120	-0.009	-0.329	0.106	-0.064	-0.022	-0.077	-0.129	-0.049	

Table 5: Portfolio Returns Sorted by β^{spc}

This table shows the results of univariate portfolio analysis. At the end of each month t, stocks are sorted into 10 groups based on ascending order of β^{spc}. Then, for each portfolio, the equal-weighted and value-weighted excess returns in month t+1 are calculated. The table shows 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 factor models, which 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). The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 20^{th} cut-off at the end of each month.

Panel A: Equal-weighted return

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw (%)	0.95	0.88	0.92	0.86	0.79	0.77	0.77	0.73	0.67	0.43	-0.51***
	(2.28)	(2.59)	(2.94)	(3.01)	(2.85)	(2.75)	(2.57)	(2.34)	(1.97)	(0.96)	(-2.82)
CAPM α (%)	0.01	0.14	0.22	0.22	0.16	0.14	0.12	0.05	-0.08	-0.50	-0.51***
	(0.06)	(1.01)	(1.42)	(1.57)	(1.20)	(0.92)	(0.79)	(0.38)	(-0.64)	(-2.35)	(-2.66)
FF3 α (%)	0.02	0.11	0.17	0.17	0.12	0.09	0.07	0.01	-0.10	-0.49	-0.52***
	(0.17)	(1.32)	(1.86)	(2.33)	(1.39)	(1.07)	(0.92)	(0.09)	(-1.39)	(-3.69)	(-2.62)
FFC α (%)	0.18	0.17	0.23	0.20	0.15	0.13	0.11	0.06	-0.07	-0.44	-0.62***
	(1.66)	(2.29)	(2.67)	(2.71)	(1.93)	(1.70)	(1.31)	(0.90)	(-0.90)	(-3.49)	(-3.35)
FF5 α (%)	0.26	0.11	0.10	0.05	0.04	-0.02	-0.01	-0.04	-0.12	-0.26	-0.51**
	(1.81)	(1.31)	(1.35)	(0.87)	(0.57)	(-0.32)	(-0.19)	(-0.60)	(-1.64)	(-2.17)	(-2.50)
FF6 α (%)	0.36	0.16	0.15	0.08	0.08	0.01	0.02	-0.00	-0.10	-0.23	-0.59***
	(3.03)	(2.14)	(2.25)	(1.35)	(1.08)	(0.23)	(0.19)	(-0.01)	(-1.26)	(-1.98)	(-3.20)
Q5 α (%)	0.47	0.20	0.14	0.10	0.11	0.04	0.06	0.06	0.02	-0.09	-0.55**
	(2.98)	(2.24)	(1.56)	(1.21)	(1.23)	(0.40)	(0.67)	(0.82)	(0.31)	(-0.78)	(-2.58)

Panel B: Value-weighted return

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw (%)	1.01	0.81	0.70	0.64	0.56	0.62	0.56	0.65	0.61	0.27	-0.74***
	(2.28)	(2.28)	(2.69)	(2.42)	(2.07)	(2.38)	(1.97)	(2.30)	(1.94)	(0.63)	(-3.75)
CAPM α (%)	0.12	0.09	0.07	0.07	-0.02	0.06	-0.04	0.07	-0.04	-0.54	-0.66***
	(0.59)	(0.65)	(0.71)	(0.74)	(-0.29)	(0.83)	(-0.39)	(0.73)	(-0.44)	(-3.21)	(-3.05)
FF3 α (%)	0.16	0.11	0.06	0.05	-0.03	0.05	-0.05	0.06	-0.06	-0.54	-0.69***
	(1.04)	(0.86)	(0.66)	(0.64)	(-0.44)	(0.68)	(-0.50)	(0.68)	(-0.55)	(-3.23)	(-3.42)
FFC α (%)	0.26	0.18	0.10	0.05	-0.02	0.02	-0.08	0.04	-0.06	-0.45	-0.70***
	(1.64)	(1.40)	(1.01)	(0.61)	(-0.24)	(0.33)	(-0.74)	(0.46)	(-0.60)	(-2.73)	(-3.23)
FF5 α (%)	0.42	0.18	0.07	-0.09	-0.03	-0.03	-0.10	-0.01	-0.13	-0.31	-0.73***
	(2.70)	(1.28)	(0.85)	(-1.11)	(-0.49)	(-0.37)	(-1.16)	(-0.11)	(-1.06)	(-2.14)	(-3.40)
FF6 α (%)	0.48	0.23	0.10	-0.08	-0.02	-0.04	-0.12	-0.02	-0.13	-0.25	-0.73***
	(3.18)	(1.63)	(1.12)	(-1.04)	(-0.34)	(-0.53)	(-1.22)	(-0.23)	(-1.07)	(-1.72)	(-3.31)
Q5 α (%)	0.49	0.19	0.07	-0.06	-0.02	-0.12	-0.14	-0.00	-0.10	-0.20	-0.69***
	(3.04)	(1.36)	(0.74)	(-0.75)	(-0.31)	(-1.47)	(-1.38)	(-0.04)	(-0.81)	(-1.24)	(-2.98)

Table 6: Factor Loadings of β^{spc}-sorted High-minus-low Returns

This table shows the regression results of the β^{spc}-sorted high-minus-low return 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. Note that the SMB in FF3 and FFC models are different from that in FF5 and FF6 models due to different construction methods. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The data for month t+1 high-minus-low return and factor returns ranges from Jan 1997 to Jan 2020.

Panel A: Dependent variable=high-minus-low return spread (equal-weighted) in percentage

	CAPM	FF3	FFC	FF5	FF6		Q5
Alpha	-0.507***	-0.516***	-0.616***	-0.514**	-0.589***	Alpha	-0.553**
	(-2.66)	(-2.62)	(-3.35)	(-2.50)	(-3.20)		(-2.58)
MKT	-0.009	-0.027	0.034	-0.026	0.023	R_MKT	-0.013
	(-0.14)	(-0.48)	(0.62)	(-0.48)	(0.41)		(-0.22)
SMB		0.127	0.108	0.097	0.067	R_ME	0.152
		(1.26)	(1.24)	(1.23)	(0.85)		(1.43)
HML		0.055	0.119	0.006	0.103	R_IA	0.095
		(0.56)	(1.29)	(0.05)	(0.92)		(0.70)
RMW				-0.076	-0.115	R_ROE	0.044
				(-0.58)	(-0.98)		(0.38)
CMA				0.122	0.086	R_EG	-0.024
				(0.91)	(0.71)		(-0.19)
UMD			0.150***		0.153***		
			(2.65)		(2.67)		
Adj.R^2	-0.35%	0.98%	6.84%	1.14%	7.20%	Adj.R^2	1.43%
N	277	277	277	277	277	N	277

Panel B: Dependent variable=high-minus-low return spread (value-weighted) in percentage

	CAPM	FF3	FFC	FF5	FF6		Q5
Alpha	-0.657***	-0.693***	-0.703***	-0.725***	-0.732***	Alpha	-0.686***
	(-3.05)	(-3.42)	(-3.23)	(-3.40)	(-3.31)		(-2.98)
MKT	-0.127	-0.100	-0.093	-0.082	-0.078	R_MKT	-0.102
	(-1.30)	(-1.20)	(-1.22)	(-0.93)	(-0.95)		(-1.22)
SMB		-0.030	-0.032	-0.042	-0.045	R_ME	-0.017
		(-0.21)	(-0.23)	(-0.33)	(-0.32)		(-0.17)
HML		0.251**	0.258**	0.190	0.198	R_IA	0.331**
		(2.16)	(2.15)	(1.50)	(1.46)		(2.05)
RMW				-0.040	-0.043	R_ROE	-0.054
				(-0.24)	(-0.25)		(-0.31)
CMA				0.201	0.198	R_EG	-0.034
				(1.14)	(1.16)		(-0.14)
UMD			0.016		0.013		
			(0.16)		(0.13)		
Adj.R^2	1.62%	5.05%	4.73%	4.96%	4.63%	Adj.R^2	2.92%
N	277	277	277	277	277	N	277

Table 7: Characteristics of β^{spc}-sorted Portfolios

This table shows the average characteristics of β^{spc}-sorted portfolios. At the end of each month t, stocks are sorted into 10 groups based on ascending order of β^{spc}. Then, for each stock characteristic, its month-t equal-weighted average value across stocks within each β^{spc}-sorted portfolio is calculated. The table presents the time-series averages of each portfolio's characteristics and the average characteristics difference between high-β^{spc} and low-β^{spc} portfolios (H-L). The t-statistics for the H-L in the last column are adjusted according to Newey and West (1987) with 6 lags. The sample ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 20th cut-off at the end of each month.

	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)
β^{spc}	-0.111	-0.054	-0.033	-0.018	-0.006	0.005	0.017	0.032	0.052	0.107	0.219***	(17.65)
β^{capm}	1.302	1.113	1.047	1.007	0.988	0.985	0.991	1.025	1.089	1.261	-0.042	(-1.61)
β^{vix}	0.001	0.001	0.001	0.001	0.000	0.001	0.000	0.001	0.001	0.001	-0.000	(-0.83)
BM	0.543	0.539	0.549	0.546	0.547	0.544	0.543	0.544	0.535	0.542	-0.001	(-0.05)
SIZE	4428.7	7094.8	8779.1	10286.3	11205.5	11715.6	11217.9	9352.9	7235.0	4327.5	-101.2	(-0.37)
MOM	0.352	0.220	0.191	0.179	0.175	0.174	0.173	0.186	0.196	0.267	-0.085**	(-2.15)
REV	0.031	0.019	0.017	0.016	0.015	0.015	0.014	0.014	0.015	0.023	-0.008	(-1.28)
ILLIQ	0.024	0.016	0.017	0.017	0.022	0.020	0.018	0.021	0.020	0.025	0.001	(0.18)
IVOL	0.025	0.019	0.017	0.016	0.015	0.015	0.016	0.017	0.019	0.025	0.000	(0.65)
AG	0.300	0.205	0.186	0.172	0.161	0.161	0.170	0.175	0.204	0.281	-0.020	(-0.77)
OPR	0.158	0.174	0.176	0.177	0.178	0.177	0.175	0.172	0.169	0.150	-0.008**	(-2.10)

Table 8: Portfolio Returns Sorted by β^{spc}: Control for Other Variables

This table shows the results of bivariate portfolio analysis. At the end of each month t, stocks are first sorted into 10 groups based on the control variables one at a time, and then within each control group, stocks are further sorted into 10 groups based on ascending order of β^{spc}. The equal-weighted and value-weighted excess returns in month t+1 for each of the 10*10 portfolios are calculated. For each β^{spc} group, its return is the average month t+1 return across 10 control groups, and their time-series averages are shown *in percentage* in the table. The table also reports the high-minus-low return (H-L), its alpha adjusted for Fama-French five-factor plus momentum model (FF6 α), and their t-statistics. The t-statistics are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 20th cut-off at the end of each month.

Panel A: Equal-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)	FF6 α	t(FF6 α)
β^{capm}	0.98	0.87	0.87	0.86	0.79	0.80	0.70	0.71	0.67	0.49	-0.49***	(-2.85)	-0.50***	(-2.94)
β^{vix}	0.99	0.87	0.87	0.85	0.77	0.76	0.80	0.70	0.72	0.42	-0.57***	(-3.52)	-0.61***	(-3.62)
BM	1.01	0.94	0.86	0.87	0.88	0.78	0.76	0.77	0.68	0.57	-0.43***	(-2.93)	-0.55***	(-3.46)
SIZE	1.00	0.79	0.90	0.88	0.84	0.78	0.74	0.74	0.64	0.45	-0.56***	(-3.15)	-0.64***	(-3.57)
MOM	0.88	0.88	0.89	0.86	0.82	0.78	0.79	0.76	0.67	0.48	-0.39***	(-2.67)	-0.44***	(-2.76)
REV	1.01	0.84	0.85	0.82	0.84	0.76	0.76	0.72	0.67	0.47	-0.54***	(-3.82)	-0.59***	(-3.86)
ILLIQ	0.99	0.84	0.91	0.84	0.85	0.80	0.72	0.76	0.68	0.42	-0.57***	(-3.59)	-0.65***	(-3.83)
IVOL	0.98	0.85	0.86	0.77	0.80	0.82	0.74	0.66	0.74	0.52	-0.47***	(-3.48)	-0.53***	(-3.67)
AG	1.05	0.88	0.90	0.89	0.75	0.85	0.73	0.76	0.73	0.54	-0.50***	(-3.04)	-0.60***	(-3.57)
OPR	1.00	0.94	0.85	0.87	0.77	0.81	0.74	0.68	0.69	0.46	-0.54***	(-3.30)	-0.67***	(-3.52)

Panel B: Value-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)	FF6 α	t(FF6 α)
β^{capm}	0.97	0.66	0.75	0.72	0.66	0.66	0.57	0.61	0.67	0.33	-0.64***	(-3.92)	-0.62***	(-3.44)
β^{vix}	0.91	0.83	0.65	0.74	0.53	0.63	0.66	0.64	0.63	0.30	-0.62***	(-3.96)	-0.61***	(-3.49)
BM	0.98	0.93	0.78	0.64	0.68	0.72	0.59	0.66	0.64	0.49	-0.50***	(-2.92)	-0.55***	(-2.83)
SIZE	1.00	0.79	0.91	0.87	0.84	0.77	0.74	0.74	0.64	0.43	-0.57***	(-3.17)	-0.65***	(-3.54)
MOM	0.83	0.75	0.89	0.65	0.65	0.68	0.64	0.60	0.63	0.33	-0.50***	(-3.31)	-0.53***	(-2.94)
REV	0.99	0.77	0.80	0.67	0.64	0.60	0.63	0.61	0.64	0.41	-0.59***	(-3.86)	-0.65***	(-3.53)
ILLIQ	1.00	0.83	0.89	0.81	0.83	0.79	0.67	0.72	0.64	0.43	-0.57***	(-3.31)	-0.58***	(-3.16)
IVOL	1.02	0.77	0.74	0.60	0.64	0.59	0.61	0.59	0.69	0.33	-0.69***	(-4.40)	-0.72***	(-3.76)
AG	0.99	0.89	0.83	0.63	0.59	0.70	0.64	0.63	0.61	0.44	-0.55***	(-3.43)	-0.66***	(-3.47)
OPR	0.94	0.90	0.71	0.59	0.61	0.66	0.67	0.53	0.48	0.30	-0.63***	(-3.19)	-0.84***	(-3.84)

Table 9: Fama-Macbeth Regression

This table shows the Fama and Macbeth (1973) regression of month t+1 stock excess return (in percentage) on the β^{spc} and control variables at the end of month t. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The "Ln()" means the natural log transformation. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 20th cut-off at the end of each month.

	Dependent variable: R_{t+1}^{i} in percentage			
	(1)	(2)	(3)	(4)
β^{spc}	-2.990***	-2.893***	-2.775***	-1.937***
	(-3.23)	(-3.36)	(-3.34)	(-2.80)
β^{capm}		-0.005	0.013	-0.009
		(-0.01)	(0.04)	(-0.03)
β^{vix}			3.428	-4.266
			(0.52)	(-0.70)
Ln(BM)				-0.018
				(-0.21)
Ln(SIZE)				-0.096*
				(-1.97)
MOM				-0.038
				(-0.13)
REV				-1.407**
				(-2.13)
ILLIQ				3.554
				(0.40)
IVOL				-5.979
				(-0.87)
AG				-0.328***
				(-3.83)
OPR				1.378***
				(2.72)
Intercept	0.779**	0.804***	0.797***	1.240**
	(2.43)	(3.09)	(3.11)	(2.40)
Observations	531483	531483	531483	345587
adj. R^2	0.3%	4.7%	5.0%	9.2%

Table 10: Predicting Stock Returns at Longer Horizons

This table shows the Fama and Macbeth (1973) regression coefficients of stock excess return from month t+1 to t+h (both inclusively) on β^{spc} at the end of month t, with each row representing one of the four specifications in Table 9. The coefficients on control variables are omitted for simplicity. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 20th cut-off at the end of each month.

	Fama-Macbeth regression coefficients of $R^i_{t\to t+h}$ (in percentage) on β^{spc}			
	h=3	h=6	h=9	h=12
(1)	-5.697**	-8.587**	-8.405*	-11.937*
	(-2.55)	(-2.50)	(-1.67)	(-1.95)
(2)	-6.085***	-10.067***	-11.491**	-15.967***
	(-3.00)	(-3.21)	(-2.49)	(-2.79)
(3)	-5.988***	-9.797***	-11.117**	-15.725***
	(-3.01)	(-3.16)	(-2.45)	(-2.79)
(4)	-4.067**	-5.959**	-5.413	-7.204
	(-2.47)	(-2.09)	(-1.19)	(-1.21)

Table 11: Robustness of Alternative spc

This table shows the robustness of time-series predictive regression with alternative spc. We regress future 1-year market excess return ($R^M_{t,t+252}$ in Table 2, and $R^M_{s,s+12}$ in Table 3) on alternative spc, with or without control variables. The alternative spc is now the slope of put-over-call implied volatility ratio at strike $K = S\exp(rT)$, with the implied volatility interpolated from Volatility Surface ($spc_t^{interp\_VS}$), or from option trading data ($spc_t^{interp\_TR}$). As for the controls, RBound is the lower bound of 1-year expected market excess return at daily frequency in Martin (2017), while "All Sig." means that we simultaneously control for all other time-series predictors in Table 3 that are significant in the bivariate regression with spc (we exclude dp for the same reason as Table 3). The Newey and West (1987) t-statistics with lags equal to the predictive horizon are reported in parenthesis (252 lags for the daily frequency and 12 lags for the monthly frequency). The data ranges from Jan 1996 to Dec 2019.

	$X_t = spc_t^{interp\_VS}$				$X_t = spc_t^{interp\_TR}$			
	Daily Frequency		Monthly Frequency		Daily Frequency		Monthly Frequency	
	$R^M_{t,t+252}$	$R^M_{t,t+252}$	$R^M_{s,s+12}$	$R^M_{s,s+12}$	$R^M_{t,t+252}$	$R^M_{t,t+252}$	$R^M_{s,s+12}$	$R^M_{s,s+12}$
Const.	0.085***	0.011	0.084***	1.756**	0.084***	0.011	0.082***	1.736**
	(3.05)	(0.25)	(3.01)	(2.41)	(2.99)	(0.25)	(2.93)	(2.31)
X_t	-0.509**	-0.582**	-0.905***	-0.697**	-0.321**	-0.368**	-0.676***	-0.548**
	(-2.04)	(-2.19)	(-3.05)	(-2.20)	(-2.22)	(-2.29)	(-2.94)	(-2.40)
Control								
RBound		√				√		
All Sig.				√				√
Adj. R^2	0.94%	5.98%	2.70%	42.1%	0.63%	5.57%	2.69%	41.34%
N	6040	6040	288	288	6040	6040	288	288

Table 12: Robustness of Alternative Slope Betas

This table shows the main cross-sectional results for alternative slope betas. In the first two columns, we estimate slope beta as stock's exposure to the alternative spc in Table 11, denoted by $\beta^{spc}_{interp\_VS}$ and $\beta^{spc}_{interp\_TR}$, respectively. In the next three columns, we estimate slope beta as stock's exposure to spc innovations rather than spc levels, where the 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 ($\beta^{spc}_{Expand\_AR}$). In the next five columns, the slope betas are estimated with different factor returns as control, instead of the Carhart 4 factors. In the last two columns, we exclude 10-days maturity or exclude maturities above 1 year in spc construction, and then estimate slope beta accordingly (β^{spc}_{ex10} and $\beta^{spc}_{ex\geq 1Y}$). Panel A presents the high-minus-low return spread (H-L) and its 6-factor alpha (FF6 α) in the univariate sort by these alternative slope betas, while Panel B summarizes the Fama-Macbeth regression coefficients of month t+1 stock excess return on these alternative slope betas at the end of month t, with each row representing one of the four different regression specifications in Table 9. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 20th cut-off at the end of each month.

Panel A: High-minus-low return spread of univariate sort by alternative β^{spc}

	$\beta^{spc}_{interp\_VS}$	$\beta^{spc}_{interp\_TR}$	$\beta^{spc}_{Full\_AR}$	$\beta^{spc}_{Roll\_AR}$	$\beta^{spc}_{Expand\_AR}$	β^{spc}_{MKT}	β^{spc}_{FF3}	β^{spc}_{FF5}	β^{spc}_{FF6}	β^{spc}_{Q5}	β^{spc}_{ex10}	$\beta^{spc}_{ex\geq 1Y}$
						Equal-weighted						
H-L (%)	-0.53***	-0.53***	-0.46***	-0.37**	-0.44**	-0.41*	-0.43**	-0.38*	-0.50***	-0.31*	-0.52***	-0.47***
	(-2.88)	(-2.93)	(-2.62)	(-2.20)	(-2.40)	(-1.77)	(-2.09)	(-1.94)	(-2.73)	(-1.75)	(-2.81)	(-2.94)
FF6 α (%)	-0.61***	-0.59***	-0.52***	-0.51***	-0.53***	-0.57**	-0.58***	-0.40*	-0.48***	-0.29*	-0.59***	-0.53***
	(-3.19)	(-3.07)	(-2.86)	(-2.82)	(-2.79)	(-2.42)	(-2.61)	(-1.97)	(-2.61)	(-1.70)	(-3.10)	(-3.13)
						Value-weighted						
H-L (%)	-0.73***	-0.78***	-0.52**	-0.57**	-0.52**	-0.23	-0.51**	-0.40**	-0.60***	-0.26	-0.76***	-0.59***
	(-3.64)	(-3.72)	(-2.36)	(-2.44)	(-2.30)	(-0.77)	(-2.27)	(-1.99)	(-2.92)	(-1.15)	(-3.94)	(-3.25)
FF6 α (%)	-0.69***	-0.80***	-0.65**	-0.64**	-0.64**	-0.40	-0.62**	-0.37	-0.49**	-0.17	-0.75***	-0.66***
	(-2.79)	(-2.92)	(-2.48)	(-2.27)	(-2.38)	(-1.28)	(-2.36)	(-1.47)	(-2.12)	(-0.76)	(-3.48)	(-3.05)

Panel B: Fama-Macbeth regression on alternative β^{spc} under different regression specifications in Table 9

	$\beta^{spc}_{interp\_VS}$	$\beta^{spc}_{interp\_TR}$	$\beta^{spc}_{Full\_AR}$	$\beta^{spc}_{Roll\_AR}$	$\beta^{spc}_{Expand\_AR}$	β^{spc}_{MKT}	β^{spc}_{FF3}	β^{spc}_{FF5}	β^{spc}_{FF6}	β^{spc}_{Q5}	β^{spc}_{ex10}	$\beta^{spc}_{ex\geq 1Y}$
(1)	-3.096***	-4.009***	-2.121***	-1.926**	-2.175***	-2.328**	-2.506**	-2.028*	-2.756***	-1.679*	-2.666***	-5.269***
	(-3.13)	(-3.41)	(-2.66)	(-2.54)	(-2.73)	(-2.07)	(-2.32)	(-1.95)	(-2.87)	(-1.95)	(-3.03)	(-3.38)
(2)	-3.000***	-3.802***	-1.902**	-1.906***	-2.007***	-2.498**	-2.609**	-2.228**	-2.739***	-1.782**	-2.567***	-5.270***
	(-3.25)	(-3.45)	(-2.54)	(-2.60)	(-2.67)	(-2.56)	(-2.59)	(-2.29)	(-3.07)	(-2.12)	(-3.14)	(-3.54)
(3)	-2.876***	-3.662***	-1.832**	-1.857***	-1.932***	-2.399**	-2.522**	-2.122**	-2.612***	-1.652**	-2.463***	-5.072***
	(-3.23)	(-3.41)	(-2.52)	(-2.61)	(-2.66)	(-2.49)	(-2.59)	(-2.24)	(-3.01)	(-2.01)	(-3.13)	(-3.47)
(4)	-1.996***	-2.211**	-1.178*	-1.278**	-1.262**	-1.975**	-1.828**	-1.681**	-1.916**	-1.305*	-1.648**	-3.811***
	(-2.70)	(-2.43)	(-1.91)	(-2.22)	(-2.07)	(-2.53)	(-2.32)	(-2.15)	(-2.59)	(-1.86)	(-2.57)	(-3.01)

Table 13: spc_i from Individual Stock Options

This table shows the Fama and Macbeth (1973) regression of month t+1 stock excess return (in percentage) on the spc_i, β^{slope}, and control variables at the end of month t, where spc_i is the slope of at-the-money put-over-call implied volatility ratio extracted from individual stock options. The control variables in the first four columns and column 6 to 9 are same as the four regression specifications in Table 9. In column 5 and 10, we add three additional option-based predictors as controls, including implied volatility skew (IVSKEW), implied volatility spread (IVSPREAD), and risk-neutral skewness (RNS). All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks that are above NYSE size 20th cut-off and have valid spc_i at the end of each month.

	Dependent variable: R_{t+1}^{i} in percentage									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
spc_i	2.638**	2.568***	2.470***	2.516***	-0.852	2.619**	2.577***	2.483***	2.528***	-0.86
	(2.45)	(3.31)	(3.22)	(3.68)	(-1.51)	(2.41)	(3.28)	(3.20)	(3.65)	(-1.53)
β^{spc}						-2.681***	-2.594***	-2.482***	-1.732**	-1.703**
						(-2.81)	(-2.98)	(-2.97)	(-2.52)	(-2.47)
IVSKEW					-0.714*					-0.739*
					(-1.84)					(-1.91)
IVSPREAD					-4.631***					-4.632***
					(-5.12)					(-5.12)
RNS					0.220**					0.211**
					(2.15)					(2.12)
Control										
β^{capm}		√	√	√	√		√	√	√	√
β^{vix}			√	√	√			√	√	√
Characteristics				√	√				√	√
Observations	452494	452494	452494	310554	310553	452494	452494	452494	310554	310553

Internet Appendix for "Slope Beta and Cross-Sectional Stock Returns"

A. Open Source Asset Pricing Data

The open source asset pricing website of Chen and Zimmermann provides code to obtain data for a comprehensive list of stock characteristics conveniently. To get the monthly data of stock return and control variables, we run the "dl_signals_add_crsp.R" file in https://github.com/OpenSourceAP/CrossSectionDemos with data release to be 2022 March. The output contains 5056633 observations. The stock returns are not in the output in default and therefore we add a line (line 129) to the original code to obtain the monthly stock returns:

```
123 # NOTE THESE ARE SIGNED!
124 # change the following to add ret to output
125 crspmsignal = crspm2 %>%
126   transmute(
127     permno
128     , yyyymm
129     , ret
130     , STreversal = -1*if_else(is.na(ret), 0, ret)
131     , Price = -1*log(abs(prc))
132     , Size = -1*log(me)
133   )
```

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 open source dataset are already matched to each month end by considering lags and the monthly stock returns are already adjusted for delisting.

B. Details of Control Variables

In the followings, we provide detailed descriptions about the control variables we use in the cross-sectional analysis, and how we obtain them from 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^{slope} 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 past one-month daily data.

SIZE: the market capitalization at each month end, in millions of dollars.

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

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

REV: reversal in Jegadeesh (1990), defined as return of the previous month.

ILLIQ: illiquidity in Amihud (2002), defined as daily absolute return divided by daily dollar trading volume (in millions of dollars), averaged over past 12 months.

IVOL: idiosyncratic volatility in Ang, Hodrick, Xing, and Zhang (2006), defined as standard deviation of the residual returns with respect to Fama-French three-factor model. It is estimated using daily data in the past one month.

AG: annual growth rate of total asset in Fama and French (2015).

OPR: R&D-adjusted operating profitability in Ball, Gerakos, Linnainmaa, and Nikolaev (2015), defined as revenue minus cost of goods sold, minus selling, general, and administrative expenses, plus research and development expense, then divided by total asset.

All these control variables except CAPM beta are fetched from the open source dataset in the Internet Appendix A with some small modifications, which are described in the following table. For the CAPM beta, we calculate it ourselves since we cannot find the exact correspondence we need[1], but the results are robust to the beta in 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	β^{vix}=-betaVIX
BM	BMdec	BM=BMdec; if BM<=0, then set it to missing
SIZE	Size	SIZE=exp(-Size)/1000
MOM	Mom12	MOM=Mom12
REV	STreversal	REV=-STreversal/100
IVOL	IdioVol3F	IVOL=-IdioVol3F
ILLIQ	Illiquidity	ILLIQ=Illiquidity*1000000
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 and above-NYSE-size-50th sample to show that our results are robust. The results are significant in both samples.

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

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

This table shows the results of univariate portfolio analysis for the all-stocks sample. At the end of each month t, stocks are sorted into 10 groups based on ascending order of β^{spc}. Then, for each portfolio, the equal-weighted and value-weighted excess returns in month t+1 are calculated. The table shows 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, which include CAPM, Fama-French three-factor and five-factor models (FF3 and FF5), and 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 parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 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

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw (%)	0.90	1.12	1.00	0.95	0.97	0.79	0.82	0.72	0.62	0.31	-0.59***
	(1.65)	(2.64)	(2.70)	(2.82)	(3.05)	(2.56)	(2.51)	(2.05)	(1.52)	(0.55)	(-3.66)
CAPM α (%)	-0.01	0.36	0.32	0.31	0.36	0.18	0.18	0.04	-0.16	-0.61	-0.60***
	(-0.02)	(1.53)	(1.47)	(1.66)	(1.97)	(1.02)	(1.09)	(0.22)	(-0.80)	(-1.86)	(-3.65)
FF3 α (%)	-0.01	0.33	0.27	0.26	0.31	0.13	0.14	0.00	-0.19	-0.60	-0.59***
	(-0.05)	(2.17)	(2.06)	(2.56)	(3.04)	(1.37)	(1.48)	(0.02)	(-1.79)	(-2.62)	(-3.48)
FFC α (%)	0.32	0.52	0.38	0.38	0.41	0.23	0.24	0.14	-0.03	-0.33	-0.64***
	(1.28)	(3.46)	(3.16)	(3.72)	(4.20)	(2.29)	(2.66)	(1.47)	(-0.26)	(-1.25)	(-3.89)
FF5 α (%)	0.33	0.48	0.28	0.22	0.27	0.10	0.13	0.04	-0.06	-0.21	-0.54***
	(1.16)	(2.69)	(2.01)	(2.05)	(2.58)	(0.98)	(1.23)	(0.41)	(-0.46)	(-0.83)	(-3.13)
FF6 α (%)	0.56	0.61	0.37	0.31	0.34	0.17	0.20	0.14	0.05	-0.02	-0.58***
	(2.12)	(3.85)	(3.10)	(3.21)	(3.74)	(1.84)	(2.19)	(1.42)	(0.35)	(-0.09)	(-3.60)
Q5 α (%)	0.75	0.66	0.38	0.34	0.38	0.21	0.29	0.22	0.20	0.14	-0.61***
	(2.40)	(3.45)	(2.49)	(2.58)	(2.94)	(1.42)	(2.21)	(1.51)	(1.09)	(0.46)	(-3.34)

Panel B: Value-weighted return

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw (%)	0.96	0.96	0.88	0.73	0.63	0.60	0.61	0.57	0.47	-0.03	-0.99***
	(1.91)	(2.53)	(2.77)	(2.87)	(2.36)	(2.27)	(2.21)	(1.95)	(1.30)	(-0.06)	(-3.74)
CAPM α (%)	-0.06	0.19	0.20	0.15	0.06	0.02	0.02	-0.04	-0.23	-0.97	-0.92***
	(-0.19)	(1.40)	(1.79)	(1.75)	(0.70)	(0.24)	(0.35)	(-0.52)	(-1.69)	(-4.41)	(-3.09)
FF3 α (%)	-0.02	0.20	0.19	0.14	0.04	0.01	0.02	-0.05	-0.23	-0.96	-0.94***
	(-0.08)	(1.69)	(1.73)	(1.64)	(0.57)	(0.10)	(0.30)	(-0.68)	(-1.67)	(-4.68)	(-3.29)
FFC α (%)	0.17	0.30	0.24	0.16	0.05	0.00	-0.01	-0.09	-0.19	-0.88	-1.06***
	(0.82)	(2.44)	(2.11)	(1.86)	(0.58)	(0.02)	(-0.08)	(-1.14)	(-1.46)	(-4.43)	(-3.81)
FF5 α (%)	0.33	0.32	0.19	0.06	-0.01	-0.05	-0.02	-0.11	-0.19	-0.66	-1.00***
	(1.35)	(2.36)	(1.73)	(0.84)	(-0.16)	(-0.74)	(-0.28)	(-1.35)	(-1.27)	(-3.72)	(-3.26)
FF6 α (%)	0.46	0.39	0.23	0.08	-0.01	-0.05	-0.03	-0.14	-0.17	-0.62	-1.08***
	(2.10)	(2.88)	(2.09)	(1.08)	(-0.09)	(-0.74)	(-0.51)	(-1.70)	(-1.14)	(-3.37)	(-3.74)
Q5 α (%)	0.57	0.33	0.16	0.06	-0.02	-0.12	-0.06	-0.12	-0.08	-0.55	-1.11***
	(2.25)	(2.42)	(1.47)	(0.65)	(-0.31)	(-1.61)	(-0.73)	(-1.47)	(-0.54)	(-2.68)	(-3.38)

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

This table shows the results of bivariate portfolio analysis for the all-stocks sample. At the end of each month t, stocks are first sorted into 10 groups based on the control variables one at a time, and then within each control group, stocks are further sorted into 10 groups based on ascending order of β^{spc}. The equal-weighted and value-weighted excess returns in month t+1 for each of the 10*10 portfolios are calculated. For each β^{spc} group, its return is the average month t+1 return across 10 control groups, and their time-series averages are shown *in percentage* in the table. The table also shows the high-minus-low return (H-L), its alpha adjusted for Fama-French five-factor plus momentum model (FF6 α), and their t-statistics. The t-statistics are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 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	t(H-L)	FF6 α	t(FF6 α)
β^{capm}	0.94	1.12	0.96	0.94	0.97	0.83	0.78	0.69	0.65	0.30	-0.63***	(-3.82)	-0.63***	(-4.01)
β^{vix}	0.95	1.01	0.96	0.91	0.98	0.84	0.76	0.78	0.63	0.36	-0.59***	(-4.14)	-0.57***	(-4.00)
BM	1.02	1.14	1.02	0.94	0.99	0.90	0.86	0.80	0.77	0.46	-0.57***	(-3.98)	-0.59***	(-3.91)
SIZE	0.82	0.96	1.07	0.98	0.92	0.90	0.85	0.79	0.58	0.31	-0.51***	(-3.30)	-0.53***	(-3.43)
MOM	0.91	0.93	1.00	0.94	0.93	0.80	0.83	0.75	0.73	0.41	-0.50***	(-3.95)	-0.53***	(-3.96)
REV	0.92	0.96	0.96	1.00	0.94	0.87	0.83	0.74	0.71	0.27	-0.65***	(-4.33)	-0.69***	(-4.45)
ILLIQ	0.83	1.10	0.99	0.98	0.92	0.94	0.81	0.76	0.65	0.27	-0.56***	(-3.55)	-0.58***	(-3.80)
IVOL	1.01	0.93	0.95	0.86	0.94	0.81	0.82	0.71	0.65	0.50	-0.50***	(-3.98)	-0.53***	(-4.16)
AG	0.97	1.14	1.03	1.00	0.94	0.91	0.84	0.86	0.66	0.43	-0.54***	(-3.74)	-0.55***	(-3.73)
OPR	0.98	1.08	0.99	0.87	0.96	0.85	0.77	0.75	0.74	0.44	-0.55***	(-3.38)	-0.60***	(-3.62)

Panel B: Value-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)	FF6 α	t(FF6 α)
β^{capm}	0.96	0.85	0.83	0.79	0.69	0.67	0.57	0.66	0.56	0.31	-0.65***	(-3.52)	-0.62***	(-3.13)
β^{vix}	0.77	0.94	0.84	0.67	0.67	0.68	0.66	0.60	0.46	0.26	-0.51**	(-2.52)	-0.49*	(-1.95)
BM	1.21	1.00	0.94	0.76	0.69	0.70	0.69	0.61	0.62	0.16	-1.05***	(-5.41)	-1.10***	(-4.97)
SIZE	0.77	0.88	1.00	0.95	0.86	0.85	0.78	0.71	0.51	0.26	-0.51***	(-3.30)	-0.53***	(-3.28)
MOM	0.83	0.66	0.77	0.60	0.64	0.46	0.70	0.51	0.47	0.02	-0.81***	(-4.38)	-0.80***	(-3.75)
REV	1.05	0.90	0.94	0.76	0.60	0.64	0.65	0.72	0.49	0.28	-0.76***	(-4.04)	-0.83***	(-4.00)
ILLIQ	0.79	0.97	0.92	0.90	0.82	0.89	0.80	0.65	0.57	0.22	-0.57***	(-3.65)	-0.49***	(-3.20)
IVOL	0.84	0.75	0.60	0.58	0.65	0.46	0.56	0.58	0.45	0.27	-0.57***	(-3.08)	-0.60***	(-2.81)
AG	1.18	0.97	0.99	0.73	0.72	0.70	0.55	0.61	0.61	0.31	-0.86***	(-4.21)	-0.97***	(-3.99)
OPR	0.72	0.85	0.69	0.56	0.56	0.51	0.52	0.37	0.32	0.18	-0.54**	(-2.14)	-0.70***	(-2.61)

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

This table shows the Fama and Macbeth (1973) regression of month t+1 stock excess returns on the β^{spc} and control variables at the end of month t, for the all-stocks sample. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The "Ln()" means the natural log transformation. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 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}	-2.336***	-2.406***	-2.310***	-0.995*
	(-4.02)	(-4.15)	(-4.04)	(-1.91)
β^{capm}		-0.156	-0.148	0.053
		(-0.67)	(-0.64)	(0.22)
β^{vix}			-2.401	-3.391
			(-0.46)	(-0.83)
Ln(BM)				0.014
				(0.15)
Ln(SIZE)				-0.140***
				(-2.74)
MOM				0.041
				(0.13)
REV				-1.842***
				(-3.05)
ILLIQ				0.039***
				(4.54)
IVOL				-21.501***
				(-4.80)
AG				-0.596***
				(-5.68)
OPR				1.887***
				(5.16)
Intercept	0.811**	0.933***	0.934***	1.695***
	(2.14)	(2.89)	(2.91)	(3.49)
Observations	1249288	1249288	1249284	769548
adj. R^2	0.1%	1.9%	2.0%	5.4%

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

This table shows the results of univariate portfolio analysis for the above-NYSE-size-50th sample. At the end of each month t, stocks are sorted into 10 groups based on ascending order of β^{spc}. Then, for each portfolio, the equal-weighted and value-weighted excess returns in month t+1 are calculated. The table shows 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, which include CAPM, Fama-French three- and five-factor models (FF3 and FF5), and 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 parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 50th cut-off at the end of each month.

Panel A: Equal-weighted return

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw (%)	0.85	0.83	0.87	0.78	0.69	0.79	0.73	0.66	0.62	0.38	-0.47**
	(2.11)	(2.49)	(3.14)	(2.90)	(2.52)	(2.94)	(2.54)	(2.19)	(1.95)	(0.89)	(-2.57)
CAPM α (%)	-0.02	0.12	0.25	0.18	0.09	0.21	0.10	0.02	-0.06	-0.46	-0.44**
	(-0.12)	(1.15)	(2.18)	(1.57)	(0.79)	(1.50)	(0.82)	(0.13)	(-0.55)	(-2.60)	(-2.01)
FF3 α (%)	0.01	0.10	0.21	0.14	0.05	0.17	0.07	-0.02	-0.08	-0.45	-0.46**
	(0.06)	(1.13)	(2.62)	(1.79)	(0.64)	(1.77)	(0.80)	(-0.16)	(-0.90)	(-3.03)	(-2.19)
FFC α (%)	0.13	0.13	0.23	0.15	0.06	0.17	0.07	0.01	-0.06	-0.42	-0.55***
	(1.20)	(1.54)	(2.66)	(1.82)	(0.75)	(1.78)	(0.81)	(0.14)	(-0.69)	(-2.87)	(-2.74)
FF5 α (%)	0.25	0.08	0.11	-0.00	-0.06	0.02	-0.03	-0.11	-0.17	-0.26	-0.51**
	(1.84)	(0.83)	(1.63)	(-0.01)	(-0.73)	(0.24)	(-0.26)	(-1.15)	(-1.75)	(-1.86)	(-2.33)
FF6 α (%)	0.33	0.10	0.13	0.01	-0.04	0.03	-0.02	-0.09	-0.15	-0.24	-0.57***
	(2.78)	(1.12)	(1.72)	(0.10)	(-0.56)	(0.32)	(-0.21)	(-0.93)	(-1.56)	(-1.75)	(-2.75)
Q5 α (%)	0.46	0.13	0.12	0.04	-0.01	0.03	0.02	-0.02	-0.03	-0.08	-0.54**
	(2.94)	(1.51)	(1.50)	(0.54)	(-0.08)	(0.37)	(0.17)	(-0.17)	(-0.29)	(-0.62)	(-2.33)

Panel B: Value-weighted return

	Low	2	3	4	5	6	7	8	9	High	H-L
Raw (%)	0.93	0.78	0.72	0.63	0.51	0.62	0.67	0.53	0.63	0.34	-0.59***
	(2.30)	(2.23)	(2.94)	(2.40)	(1.81)	(2.30)	(2.51)	(1.88)	(2.04)	(0.88)	(-3.11)
CAPM α (%)	0.09	0.08	0.12	0.07	-0.06	0.05	0.10	-0.07	0.01	-0.39	-0.48**
	(0.59)	(0.56)	(1.09)	(0.74)	(-0.72)	(0.57)	(0.94)	(-0.72)	(0.10)	(-2.53)	(-2.43)
FF3 α (%)	0.13	0.10	0.12	0.06	-0.08	0.04	0.10	-0.07	0.00	-0.38	-0.52***
	(1.17)	(0.77)	(1.02)	(0.72)	(-0.95)	(0.46)	(0.99)	(-0.82)	(0.01)	(-2.50)	(-2.67)
FFC α (%)	0.23	0.15	0.13	0.06	-0.05	0.01	0.08	-0.10	-0.04	-0.34	-0.57***
	(2.00)	(1.24)	(1.13)	(0.62)	(-0.66)	(0.17)	(0.66)	(-1.07)	(-0.38)	(-2.24)	(-2.89)
FF5 α (%)	0.35	0.17	0.09	-0.05	-0.09	-0.02	0.03	-0.12	-0.07	-0.27	-0.62***
	(2.70)	(1.27)	(0.91)	(-0.62)	(-1.14)	(-0.27)	(0.31)	(-1.28)	(-0.66)	(-1.65)	(-2.72)
FF6 α (%)	0.41	0.21	0.11	-0.05	-0.07	-0.04	0.02	-0.14	-0.10	-0.24	-0.66***
	(3.35)	(1.61)	(1.01)	(-0.59)	(-0.89)	(-0.43)	(0.16)	(-1.45)	(-0.90)	(-1.50)	(-2.90)
Q5 α (%)	0.39	0.16	0.07	-0.04	-0.06	-0.14	-0.04	-0.11	-0.07	-0.18	-0.57**
	(2.71)	(1.28)	(0.61)	(-0.46)	(-0.78)	(-1.44)	(-0.34)	(-1.13)	(-0.63)	(-1.15)	(-2.33)

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

This table shows the results of bivariate portfolio analysis for the above-NYSE-size-50th sample. At the end of each month t, stocks are first sorted into 10 groups based on the control variables one at a time, and then within each control group, stocks are further sorted into 10 groups based on ascending order of β^{spc}. The equal-weighted and value-weighted excess returns in month t+1 for each of the 10*10 portfolios are calculated. For each β^{spc} group, its return is the average month t+1 return across 10 control groups, and their time-series averages are shown *in percentage* in the table. The table also shows the high-minus-low return (H-L), its alpha adjusted for Fama-French five-factor plus momentum model (FF6 α), and their t-statistics. The t-statistics are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 50th cut-off at the end of each month.

Panel A: Equal-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)	FF6 α	t(FF6 α)
β^{capm}	0.92	0.76	0.82	0.84	0.79	0.72	0.66	0.66	0.61	0.40	-0.52***	(-3.16)	-0.51***	(-2.81)
β^{vix}	0.86	0.79	0.88	0.81	0.67	0.77	0.71	0.65	0.64	0.43	-0.43***	(-2.91)	-0.47***	(-2.79)
BM	0.89	0.91	0.76	0.86	0.72	0.77	0.72	0.71	0.66	0.44	-0.45***	(-2.62)	-0.50**	(-2.37)
SIZE	0.84	0.83	0.85	0.71	0.84	0.75	0.73	0.71	0.50	0.45	-0.39**	(-2.06)	-0.50**	(-2.35)
MOM	0.84	0.81	0.87	0.81	0.76	0.72	0.78	0.69	0.55	0.41	-0.42***	(-2.81)	-0.48***	(-2.74)
REV	0.92	0.83	0.78	0.75	0.76	0.70	0.71	0.62	0.66	0.45	-0.46***	(-3.22)	-0.52***	(-3.18)
ILLIQ	0.85	0.86	0.84	0.79	0.76	0.70	0.82	0.66	0.54	0.42	-0.43**	(-2.53)	-0.50**	(-2.51)
IVOL	0.88	0.82	0.84	0.73	0.75	0.66	0.80	0.58	0.60	0.54	-0.33**	(-2.24)	-0.37**	(-2.28)
AG	0.92	0.86	0.85	0.80	0.74	0.74	0.73	0.64	0.65	0.52	-0.40**	(-2.38)	-0.41**	(-2.12)
OPR	0.88	0.82	0.85	0.85	0.68	0.78	0.69	0.66	0.57	0.38	-0.51***	(-2.92)	-0.67***	(-3.29)

Panel B: Value-weighted return

Control	Low	2	3	4	5	6	7	8	9	High	H-L	t(H-L)	FF6 α	t(FF6 α)
β^{capm}	1.01	0.62	0.81	0.69	0.65	0.68	0.59	0.62	0.63	0.40	-0.61***	(-3.96)	-0.58***	(-3.19)
β^{vix}	0.90	0.76	0.75	0.70	0.57	0.65	0.59	0.61	0.69	0.39	-0.52***	(-3.57)	-0.51***	(-3.04)
BM	0.95	0.85	0.71	0.73	0.61	0.70	0.65	0.62	0.58	0.50	-0.45**	(-2.57)	-0.49**	(-2.34)
SIZE	0.83	0.80	0.85	0.72	0.82	0.76	0.73	0.71	0.50	0.42	-0.41**	(-2.15)	-0.52**	(-2.43)
MOM	0.80	0.79	0.84	0.67	0.67	0.62	0.76	0.64	0.64	0.36	-0.44***	(-2.84)	-0.52***	(-2.92)
REV	0.88	0.81	0.71	0.59	0.76	0.53	0.66	0.52	0.79	0.47	-0.41***	(-2.63)	-0.48***	(-2.73)
ILLIQ	0.86	0.84	0.85	0.76	0.74	0.72	0.78	0.64	0.56	0.46	-0.40**	(-2.29)	-0.44**	(-2.11)
IVOL	0.95	0.71	0.78	0.57	0.67	0.54	0.74	0.53	0.62	0.35	-0.61***	(-3.88)	-0.62***	(-3.41)
AG	0.95	0.82	0.79	0.70	0.53	0.62	0.71	0.57	0.55	0.56	-0.39**	(-2.46)	-0.40**	(-2.12)
OPR	0.93	0.83	0.71	0.67	0.58	0.68	0.64	0.67	0.52	0.45	-0.48***	(-2.62)	-0.64***	(-2.99)

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

This table shows the Fama and Macbeth (1973) regression of month t+1 stock excess returns on the β^{spc} and control variables at the end of month t, for the above-NYSE-size-50th sample. All the independent variables are winsorized at 0.5% and 99.5% levels on a monthly basis. The "Ln()" means the natural log transformation. The t-statistics in parenthesis are adjusted according to Newey and West (1987) with 6 lags. The month-end t ranges from Dec 1996 to Dec 2019, and the sample includes only those common stocks above NYSE size 50th cut-off at the end of each month.

	Dependent variable: R^i_{t+1} in percentage			
	(1)	(2)	(3)	(4)
β^{spc}	-3.570***	-3.756***	-3.618***	-2.785***
	(-2.86)	(-3.28)	(-3.34)	(-2.99)
β^{capm}		-0.044	-0.016	-0.056
		(-0.12)	(-0.04)	(-0.17)
β^{vix}			0.909	-8.277
			(0.10)	(-1.00)
Ln(BM)				0.034
				(0.44)
Ln(SIZE)				-0.093*
				(-1.73)
MOM				0.047
				(0.15)
REV				-1.256*
				(-1.74)
ILLIQ				-49.519
				(-0.85)
IVOL				-5.622
				(-0.83)
AG				-0.259***
				(-3.04)
OPR				1.329**
				(2.11)
Intercept	0.721**	0.780***	0.767***	1.376**
	(2.37)	(2.96)	(2.95)	(2.35)
Observations	268801	268801	268801	176231
adj. R^2	0.6%	6.5%	7.0%	12.0%