# Investor Overconfidence and the Security Market Line: New Evidence from China

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**Abstract**

This paper documents a highly downward-sloping security market line (SML) in China, which is more puzzling than the typical "flattened" SML in the US, and does not reconcile with existing theories of the low-beta anomaly. We show that investor overconfidence offers some promises in resolving the puzzle in China: In the time-series dimension, the slope of the SML becomes more "inverted" when investors get more overconfident. This *dynamic* overconfidence effect is intensified with biased self-attribution. As a general symptom of overconfidence in the cross section, high-beta stocks are also the mostly heavily traded. After accounting for trading volume, there is no longer the low-beta anomaly at both the firm and portfolio levels. Mutual fund evidence reinforces the view that institutional investors actively exploit the portfolio implications of a downward-sloping SML by shying away from high-beta stocks and betting on low-beta stocks for superior performance.

**JEL Classification:** G11, G12, G15, G40

**Keywords:** Security Market Line, Beta Anomaly, Betting Against Beta, Overconfidence, Mutual Fund

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This paper documents a highly downward-sloping security market line (SML) in China, which is more puzzling than the typical "flattened" SML in the US, and does not reconcile with existing theories of the low-beta anomaly. We show that investor overconfidence offers some promises in resolving the puzzle in China: In the time-series dimension, the slope of the SML becomes more "inverted" when investors get more overconfident. This *dynamic* overconfidence effect is intensified with biased self-attribution. As a general symptom of overconfidence in the cross section, high-beta stocks are also the mostly heavily traded. After accounting for trading volume, there is no longer the low-beta anomaly at both the firm and portfolio levels. Mutual fund evidence reinforces the view that institutional investors actively exploit the portfolio implications of a downward-sloping SML by shying away from high-beta stocks and betting on low-beta stocks for superior performance.



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*High-risk firms have greater scope for overconfidence and disagreement, so we expect this source of overpricing to be greatest for high-risk firms. In these ways, overconfidence provides a natural explanation for the idiosyncratic volatility and betting-against-beta effects.*

***Daniel and Hirshleifer (2015)***

## 1. Introduction

In theory, the Sharpe (1964) and Lintner (1965) capital asset pricing model (CAPM) posits an *upward-sloping* security market line (SML). That is, differences in expected returns are compensations for different degrees of systematic risk (*i.e.*, market beta). However, for decades, the empirical evidence has proven more complicated than the theoretical projection: Market beta is "unpriced" at the *firm* level, reflecting a typical "flattened" SML in the US (Fama & French 1992).[1] At the *portfolio* level, low-beta stocks tend to outperform their high-beta counterparts on a risk-adjusted basis, leading to the so-called *low-beta anomaly* (Friend & Blume 1970; Haugen & Heins 1975; Baker et al. 2011).[2]

This paper examines the *low-beta anomaly* in the context of the Chinese stock market, the largest emerging financial market in the world. Carpenter et al. (2020) highlight the importance of exploring China's stock market and its role in fuelling the growth of the world's second-largest economy (*i.e.*, resource allocation). Liu et al. (2019) stress that it is crucial to allow for the unique features in understanding factor models in China. Following their leads, we shed new light on the CAPM model in China, the cornerstone of asset pricing. Estimating the (empirical) shape of the SML is not only crucial to our understanding of the finance theory, but also serves a number of practical purposes such as evaluating the cost of equity capital of a firm and developing investment strategies.

We document a striking "downward-sloping" SML in China, which is more puzzling than the typical "flattened" SML in the US. The slope coefficient of the SML in China has a negative value of -2.68, which is significant at the 1% level. Therefore, low-beta stocks outperform high-beta stocks on an *absolute* basis. The betting against beta (BAB) strategy is more profitable in China than in the US: The

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[1] The beta-return relation becomes even flatter after controlling for size, book-to-market ratio and other firm characteristics (Fama & French 2006; Blitz & Vidojevic 2017).

[2] More broadly, the low-beta anomaly is a pervasive phenomenon in financial markets as it is documented for multiple asset classes including international equities, treasury bonds, corporate bonds, and futures markets (Frazzini & Pedersen 2014). The *low-beta anomaly* has drawn substantial interests from academics and practitioners in recent years (Baker et al. 2011; Blitz et al. 2014; Frazzini & Pedersen 2014; Auer & Schuhmacher 2015; Schneider et al. 2015; Bali et al. 2017; Liu et al. 2018). For example, Frazzini and Pedersen (2014) propose a leveraged market-neutral BAB strategy designed for hedge funds, which levered up low-beta stocks in the long leg and deleveraged high-beta stocks in the short leg.

annualized Sharpe ratio of BAB is 0.99 in China, comparing to 0.66 in the US over the same sample period. Moreover, given the nature of an inverted SML, the BAB strategy is highly exploitable even for the most leverage-constrained investors in China (*i.e.*, mutual funds and retail investors).[3]

In principle, the strongly negative slope of the SML in China cannot be easily reconciled with existing theories of the low-risk anomaly that usually attribute to a certain type of constraints (Black 1972; Baker et al. 2011; Frazzini & Pedersen 2014; Schneider et al. 2015; Bali et al. 2017; Liu et al. 2018). These constraints can "flatten" the SML, but are unlikely to flip the "sign" of the slope of the SML (Black 1972; Jylha 2018), implying that there might be other economic mechanism(s) at work which has not been fully explored.

Recently, Daniel and Hirshleifer (2015) conjecture that investor overconfidence, manifested by excessive trading, provide a natural explanation for the betting against beta effect. Similar notion is also expressed in Baker et al. (2011).[4] Following these leads, we examine whether overconfidence can explain the puzzling SML in China. Intuitively, overconfidence may cause investors to underestimate risks and result in a higher-than-normal demand for speculative assets, especially for high-risk firms. Besides, there are also good reasons to believe that investor overconfidence is a key feature in the context of emerging markets: First, these markets are typically dominated by unsophisticated individual investors who tend to be too confident about their private information or trading skills (Han & Li 2017). Second, there are strong policy uncertainties caused by the regulatory body in emerging markets and such uncertainties tend to be underestimated by individual investors.[5]

In the time-series dimension, we provide consistent evidence that investor overconfidence is able to resolve the negative slope of the SML observed in China, complementing the existing explanations for the beta anomaly. Using market turnover as a proxy for investor overconfidence and carefully controlling for other possible economic mechanisms, we find that following high degree of investor overconfidence, the slope of the SML becomes more "inverted" while the intercept of the SML gets

[3] One thing subtle is that the profits of BAB in China stems mainly from the long leg, different from the results in the US where the abnormal returns are mainly from the short leg. See, among others, Stambaugh *et al.* (2012), Stambaugh *et al.* (2015), and Liu *et al.* (2018).
[4] Baker et al. (2011) argue that overconfidence, as a legitimate behavioural mechanism, could reconcile the documented low-beta anomaly: Overconfident investors engage in excessive trading volume and exert huge price pressure for volatile stocks, as they falsely believe in the precision of their price estimates.
[5] Despite being a legitimate mechanism, little work to date analyses the impact of investor overconfidence on the low-beta anomaly and the shape of the SML. To fill the gap, we do provide an illustrative model in **Section 4** to depict the interplay between investor overconfidence and the low-beta anomaly, with well-defined and testable implications.

more pronounced.[6] We show that a one-standard-deviation shock in turnover ratio leads to a downward adjustment of 1.84% percent for the unit-beta portfolio (*i.e.*, the slope of the SML), and an upward adjustment of 2.05% percent for the zero-beta portfolio (*i.e.*, the intercept of the SML) after accounting for other economic mechanisms. Moreover, we also document a *dynamic* overconfidence effect as investor overconfidence is amplified by self-attribution bias (Gervais & Odean 2001). Using prior market performance as a proxy for self-attribution bias, we find that the SML gets more inverted when investors become more overconfident due to biased self-attribution.

In the cross-sectional dimension, we further explore whether firm-level trading volume could also explain the low-beta anomaly in China. Prior empirical work suggests that investors who are overly confident about their information or skills tend to trade the most (Odean 1999; Barber & Odean 2000). These excessive trading, a symptom of overconfidence, leads to poor investment performance over time (Barber & Odean 2000; Grinblatt & Keloharju 2009). In that sense, stocks with the highest turnover ratio are mostly likely the assets that overconfident investors have "passions" about. Motivated by these works, we perform an extensive, firm-level "horse race" using the refined asset pricing test framework proposed in Hou and Loh (2016), which could differentiate the competing expiations on the low-beta anomaly. Results from the "horse race" seems to weigh more on the overconfidence-based explanation: Among all the (potential) economic mechanisms, the low-beta anomaly seems to be fully captured by the volume effect (*i.e.*, turnover ratio). The findings are robust at the portfolio level as well: Once we control for stock turnover, there is no longer a low-beta effect (in the bivariate portfolio sorts).

Finally, we explore the low-beta anomaly with mutual fund data in China. A key difference between an inverted SML and a "flattened" SML lies in its portfolio implication. In a market with a "flattened" SML, more constrained investors tend to hold high-beta stocks (Frazzini & Pedersen 2014). In a market with a downward-sloping SML, however, even the most leverage-constrained investors (such as mutual funds) could exploit the low-beta anomaly by tilting towards low-beta stocks without suffering "benchmark as limits to arbitrage" (Baker et al. 2011). This is confirmed by our observations that the profits (*i.e.*, alphas) of the BAB strategy in China stem mainly from the long leg of the portfolio.[7] More interestingly, we find that professional fund managers in China actively engage in low beta

[6] We control for other possible economic mechanisms (such as market volatility, funding liquidity, economic uncertainty, and portfolio rebalancing) to ensure that the observed net effect of market trading volume reflects the impact due to investor overconfidence. See **Section 5** for the detailed empirical implementation.

[7] This is in vast contrast with the results in the US where the abnormal returns stem mainly from the short leg (Stambaugh et al. 2012; Stambaugh et al. 2015; Liu et al. 2018).

strategy: After accounting for other well-known investment styles, it is clear that some fund managers actively exploit the low-beta anomaly by shying away from high-beta stocks and betting on low-beta stocks for superior performance.[8]

The structure of the paper is as follows. Section 2 documents the sample data and data sources. Section 3 describes the empirical shapes of the SML in China and in the US. Section 4 presents an illustrative model augmented with investor overconfidence to explain the puzzling SML in China. Section 5 provides time-series evidence and tests the time-series predictions of overconfidence suggested by the theoretical model. Section 6 provides cross-sectional evidence, including the BAB strategy, firm characteristics, and the performance of the beta-sorted decile portfolios. Section 7 performs further analyses and robustness checks, including the firm-level "horse race" and bivariate portfolio sorts. Section 8 explores the portfolio implications of the negatively sloped SML in China with mutual fund evidence. Section 9 concludes.

## 2. Data and Data Sources

The Chinese equity data are sourced from Thomsen Reuters Datastream, which includes a comprehensive list of Chinese A-shares free of survivorship bias. The list contains 3,100 stocks over the period from July 1996 to December 2016. Following the literature (Han & Li 2017; Liu *et al.* 2019), the monthly rate of the one-year bank time-deposit is used as the proxy for the risk-free rate in China. The risk factors in China are constructed similarly as in Fama and French (2015) by using the 2×3 double-sorted portfolios, which are formed in July each year and holds for 12 months. The size factor (SMB) is the arithmetic average of the three size factors generated in the 2×3 bivariate sorts for the value (HML), profitability (RMW), and investment (CMA) factors. The breakpoints for the size, value, profitability, and investment portfolios are determined solely by A-shares listed in Shanghai Stock Exchange and Shenzhen Main Board, which is similar to the NYSE criteria in the US. The monthly net asset values (NAV) of all Chinese actively managed open-end funds are obtained via the RESSET database, from which we recalculate the monthly returns of each fund.

[8] The strong low-beta phenomenon in the Chinese A-share market has also attracted the attention of foreign investors. For example, Robeco Asset Management has launched its Chinese A-share Conservative Equities fund for its global clients, betting on the low-risk stocks to achieve high investment performance (Source: https://www.robeco.com/en/funds/prof-glob-en-11/robeco-qi-chinese-a-share-conservative-equities-i-eur-lu1848870884.html).

The US stock data are retrieved from the CRSP database, which includes all common stocks (share codes 10 and 11) that are traded on NYSE, AMEX, and NASDAQ exchanges between July 1963 and December 2016. The US Fama-French five factors are downloaded from Ken French Data Library.

To benchmark our study with the seminal work of Frazzini and Pedersen (2014), we follow their variable construction procedure to derive market beta. In addition, we also calculate a number of firm characteristics such as the log of the market capitalization (lnME) and the log of the book-to-market equity ratio (lnBTM). Details of the variable construction procedure is documented in **A.1. Variable Definition** in the appendix.

## 3. Features of the Chinese Stock Market and the Security Market Line

### 3.1. Features of the Chinese Stock Market

China's GDP has tripled for three consecutive decades, and it has the world's second largest stock market as of 2019 (Liu et al. 2019; Carpenter et al. 2020). The sheer volume of its rapid growing economy and the domestic financial market have spurred increased attention from academia and practitioners alike.

Carpenter et al. (2020) document that it is crucial to understand the "real value" of China's stock market in fuelling the growth of the world's second-largest economy. Prior work has long focused on the distinctive features of China's domestic stock market, which are different from the developed markets. For example, the Chinese stock market is characterized by heavy regulation and frequent government interventions (Carpenter & Whitelaw 2017), making the IPO process more difficult for small private firms (Allen et al. 2014; Liu et al. 2019). From the trading perspective, short-sales of stocks were prohibited by law before 2010, and the stringent constraints on short selling (up to date) make it very difficult to arbitrage away the mispricing at the market level as well as the stock level (Mei et al. 2009). Besides, the Chinese stock market is largely "disconnected" from international markets: Despite its adoption of the qualified foreign institutional investors (QFII) program and other initiatives (*i.e.*, stock connect program), international investors holds only 3% of the total market capitalization (Carpenter et al. 2020).

The Chinese stock market is also well-known for its speculative nature with a huge amount of young and inexperienced retail investors. These individual investors contribute more than 80% of the total trading volume (Han & Li 2017). Given their strong market power, a natural conjecture is that various pricing anomalies exist in China. In the time-series dimension, Han and Li (2017), among others, document that domestic investor sentiment outperforms a number of fundamental variables in predicting the subsequent market returns in China. In the cross-sectional dimension, there are mounting empirical supports that size, value, profitability, beta, volatility, accrual, illiquidity, turnover, reversal, and lottery demand are prominent (cross-sectional) return determinants in the Chinese stock market (Chen et al. 2010; Cheung et al. 2015; Cakici et al. 2017; Nartea et al. 2017; Hsu et al. 2018). Liu et al. (2019) re-visit these anomalies and conclude that it is crucial to account for the unique features of China in understanding the factor models.

### 3.2. The Shape of the Security Market Lines in China and the US

Against the background mentioned in **Section 3.1**, we start the empirical analysis by examining the shape of the SML at the firm level. Understanding the (empirical) shape of the SML is crucial to the finance theory, because it not only (in)validates CAPM, but also serves for a number of practical purposes such as estimating cost of equity capital and developing investment strategies.

Although either a flattened or an inverted SML would lead to the low-beta anomaly (*i.e.*, low-beta stocks outperform high-beta stocks on a risk-adjusted basis), the different shape of the SML would have completely different portfolio implications. A flattened SML indicates a "similar-return-and-different-risk" anomaly, which "prevents" long-only institutional investors (*i.e.*, mutual funds) to act on the low-beta anomaly (Baker et al. 2011). On the contrary, a negatively sloped SML implies a "high-return-but-low-risk" anomaly which becomes exploitable for long-only investors (and long-and-short investors).

To detect the shape of the SML in China, we perform the Fama and MacBeth (1973) cross-sectional regression over the entire sample period from July 1996 to December 2016 (*i.e.*, 246 monthly observations). In each month the cross section of excess returns (over the risk-free rate, $RF$) are regressed on the *ex ante* market beta as defined in Frazzini and Pedersen (2014). The slope coefficients are then averaged over the entire sample periods.

$$Ret_i - RF = \underset{\substack{(4.40)\\ [3.13]}}{4.48} - \underset{\substack{(-2.70)\\ [-2.92]}}{2.68} \times \beta_i + \varepsilon_i \qquad [3.1]$$

The baseline regression result confirms a strong low-beta effect in China, as the slope coefficient has a negative value of -2.68, which is significant at the 1% level as indicated by both the Fama-MacBeth *t*-statistics (in parenthesis) and the Newey-West *t*-statistics (in brackets) based on a lag length of 12 months. This coefficient is large: a 1% decrease in the covariance with market return leads to an extra return of 2.68%. The strongly negative slope coefficient implies a downward-sloping SML. That is, the higher the market beta of a stock, the lower the expected return. High-beta stocks underperform low-beta stocks on an *absolute* (no-risk-adjusted) basis.[9]

To showcase the striking results in China, we perform a *mini* comparison by replicating the analysis on the US stocks over the *same* sample period. Similar to the findings of the US studies (Fama & French 1992), the Fama-MacBeth regression output for the US stock market indicates a typical "flattened" CAPM line, as the factor loadings on the stock beta is slightly positive, but indifferent from zero from a statistical perspective.[10]

$$Ret_i - RF = \underset{\substack{(2.98)\\ [2.13]}}{0.99} + \underset{\substack{(0.16)\\ [0.16]}}{0.10} \times \beta_i + \varepsilon_i \qquad [3.2]$$

Given the downward-sloping SML in China as opposed to the "flattened" SML in the US, it is apparent that the low-beta anomaly is much more pronounced in China than in the US.

[9] For exposition ease, we have reported mainly the slope coefficient on beta (*i.e.*, slope of SML) based on the ordinary least square (OLS) estimation method. However, we are aware of the econometric issue: The "error-in-variable" (EIV) problem in the Fama-MacBeth cross-sectional regression, because market betas are estimated. In principle, the inherent "error-in-variable" problem in the cross-sectional regression would bias upward the estimated slope of SML as compared to the true slope, making it more difficult to detect a downward sloping SML when the number of stocks in the cross section is large. To address the "error-in-variable" problem, we have adopted alternative EIV correction techniques to ensure the robustness. When adopting the Kim and Skoulakis (2018) regression-calibrated approach, the estimated $N$-consistent slope coefficient on market beta amounts to -2.37 (significant at the 1% level). Similarly, when using the Jegadeesh et al. (2019) instrumental variable (IV) approach, the $N$-consistent estimate of the slope of the SML amounts to -3.08 (significant at the 5% level). Therefore, our key finding of a downward-sloping SML in China is robust under alternative estimation methods. We are highly indebted to an anonymous referee for pointing out this econometric issue, which ensures the robustness of our finding.
To address the concern of P-hacking in Harvey (2017)'s presidential address, we have also reported the shape of the SML in China with alternative beta construction methods (see **Appendix A.3**). The results are very robust with a downward-sloping SML in China. Despite the plausibility and robustness of our finding, we should "recognize that any investigation is unlikely to yield a zero-one (false-true) outcome (Harvey 2017)." For example, based on the t-statistics of the slope coefficient on beta using the Kim and Skoulakis (2018) method and the prior on market beta as the "Solid footing" category, the associated SD-MBF (the symmetric and descending minimum Bayes factor) would be (less than) 0.11. That is, there is still a (less than) 11% probability that the null hypothesis (*i.e.*, slope coefficient on beta is zero in China) is true. As is suggested in Harvey (2017), it is more important to "focus on both the magnitude and sign of an effect, not just on the level of significance." This is because $p$-values do not tell us about the size of the economic effect. Moreover, the $p$-value should be used in conjunction with other types of evidence when available. When interpreting our empirical results (in later sections) jointly with the documented $p$-value, it lends more assurance that our paper has more merits than just confirming a downward-sloping SML, because it tackles the more important economic issues on how do we understand the downward-sloping SML, the time variation of SML, and its portfolio implications. Again, we are highly indebted to an anonymous referee for stressing this point.
[10] Note the "flattened" CAPM line is not new for the US market (see, among others, Fama and French (1992) for various sample periods).

Note that the downward-sloping SML in China remain robust as we control for other well-known cross-sectional return predictors such as size, value, profitability, investment, intermediate-term momentum, and short-term reversal in the Fama-MacBeth regression.

$$Ret_i - RF = a + b_1\beta_i + b_2 lnME_i + b_3 lnBTM_i + b_4 OP_i + b_5 INV_i + b_6 RET_i^{MOM} + b_7 RET_i^{STREV} + \varepsilon_i \quad [3.3]$$

where the log of market equity ($lnME$), the log of book-to-market equity ($lnBTM$), the ratio of operational profits and book equity ($OP$), and the growth rate of the total assets ($INV$), the intermediate-term return momentum ($RET^{MOM}$) and the short-term reversal ($RET^{STREV}$) are defined in **Appendix A1**.

**Table 1** presents the multi-variate regression outputs for China. We first include in the regression the log of market equity and the log of book-to-market equity to control for the size and value effect. The slope coefficient on the market beta becomes slightly smaller with a value of -2.05, but remains highly significant as the Fama-MacBeth *t*-statistics (in parenthesis) and the Newey-West *t*-statistics (in brackets) are -2.30 and -3.90, respectively. In the second case when the log of market equity, the log of book-to-market equity, the ratio of operational profits and book equity, and the growth rate of the total assets are simultaneously included in the regression, the slope coefficient on the market beta remains statistically significant with a value of -2.03. In the final case when the intermediate-term momentum and the short-term reversal are also included, the coefficient on beta remains strong with a value of -2.24 which is significant at 5% (1%) level indicated by the Fama-MacBeth (Newey-West) *t*-statistics. In comparison, the shape of a "flattened" CAPM line in the US also holds for alternative model specifications (see **Table A1** in appendix).

[**Insert Table 1 here**]

To summarize, we find compelling evidence that stock beta is a strong, negative return determinant at the firm level in China, indicating a highly negatively sloped SML in China. Moreover, the information content of market beta is not subsumed by the conventional (cross-sectional) return predictors including size, value, profitability, investment, intermediate-term momentum, and short-term reversal, as is indicated in the multi-variate Fama-MacBeth cross-sectional regression. From an investment perspective, the "inverted" security market line suggests the "betting against beta" strategy might be more profitable in the Chinese equity market than in the US. A more relevant and urgent task is to understand the (possible) economic mechanisms that could contribute to the negatively sloped SML in China. In fact, an "inverted" SML represents a much bigger asset-pricing puzzle than a "flattened"

SML, because it implies a negative price of risk in equilibrium which defies the traditional risk-based explanations of beta.[11]

## 4. An Illustrative Model: Investor Overconfidence and the SML

Motivated by Daniel and Hirshleifer (2015), in this section, we develop a one-period (behavioural) CAPM model to explain the low-beta anomaly, the negative relation between trading volume and the slope of the SML, and the negative-sloped SML found in the Chinese equity market. Our model depicts a representative agent who is overly confident about the (noisy) signals of the stocks she receives. As the general symptom of overconfidence, she overestimates the precision of her information, and hence underestimates volatilities. In particular, she is more confident about the precision of market information relative to firm-specific information (Peng & Xiong 2006). As a result, she underestimates risks, especially for high-beta firms (*i.e.*, high return covariance with the market), and hence demands a lower risk-adjusted return on high-beta stocks than on low-beta stocks. Sufficiently high degree of overconfidence leads to an inverted SML. The model works as follows:

Assume there are $N$ risky assets and one riskless asset with riskless rate $r_f$ in the financial market. The payoffs of the $N$ risky assets at time 1 have a common factor structure:

$$\boldsymbol{R} = \boldsymbol{a} + \boldsymbol{b}f + \boldsymbol{g}, \qquad [4.1]$$

where $f$ is a market-wide factor and $\boldsymbol{g} = (g_1, g_2, \dots, g_N)'$ is a vector of the firm-specific factors. The common and the firm-specific factors are unobservable and independent of each other. For simplicity, we assume that there is only one common factor in Equation [4.1], but our results still hold for the case with multiple common factors. The agent knows the distributions of the factors:

$$f \sim N(\mu_f, \bar{\tau}_f^{-1}), \qquad g_i \sim N(\mu_{g,i}, \bar{\tau}_{g,i}^{-1}), \qquad \text{for } i = 1, \dots, N. \qquad [4.2]$$

The agent receives signals at time 0:

$$s_f = f + v_f, \qquad s_{g,i} = g_i + v_{g,i}, \qquad [4.3]$$

where the signal noises $v_f$ and $v_{g,i}$ are assumed to follow Gaussian distributions with zero means and are independent of each other:

[11] In the US market, the slope of the SML can be also negative during certainty time periods. In fact, the risk premium can be negative when sentiment is high in the US, as empirically documented in Greenwood and Hanson (2013) and Cassella and Gulen (2018), and theoretically proved by Li and Liu (2018), implying a negative slope of the SML.

$$\upsilon_f \sim N(0, \bar{\eta}_f^{-1}\tau_f^{-1}), \qquad \upsilon_{g,i} \sim N(0, \bar{\eta}_{g,i}^{-1}\tau_{g,i}^{-1}). \qquad [4.4]$$

These signals are actually uninformative with zero precisions $\bar{\eta}_f = 0$ and $\bar{\eta}_{g,i} = 0$ (the variances of the signals are infinity).[12] However, the agent is overconfident and overestimates the informativeness of her signal (Scheinkman & Xiong 2003; Peng & Xiong 2006). She believes that these signals are informative with finite variances. Because an overconfident agent tends to process more market-level information than firm-specific information as documented in Peng and Xiong (2006), she is more overconfident about the precision of market information. Therefore,

$$\bar{\eta}_f > \bar{\eta}_{g,i} > 0.$$

The above assumption is suitable for the Chinese market.[13] Intuitively, due to lower quality of accounting information and tighter market regulations than those of developed markets, it is more difficult for investors to receive timely and accurate information in Chinese markets than in developed markets. As a result, individual investors typically obtain information by also relying on some unofficial sources and tend to overvalue the precision of such "private" information. Due to the nature of these informal information sources, even fake news or rumors may have significant effect on investors' decision making. Further, the Chinese market is dominated by unsophisticated individual investors who are more likely to believe the word-of-mouth information. In all, it is fair to assume that the investors in Chinese market tend to be more overconfident about their own information.

According to the Bayes rule, the posterior beliefs of the agent are given by

$$f|s_f \sim N(\hat{\mu}_f, \hat{\eta}_f^{-1}\tau_f^{-1}), \qquad g_i|s_{g,i} \sim N(\hat{\mu}_{g,i}, \hat{\eta}_{g,i}^{-1}\tau_{g,i}^{-1}), \qquad [4.5]$$

where $\hat{\eta}_f = 1 + \bar{\eta}_f > 1$, and $\hat{\eta}_{g,i} = 1 + \bar{\eta}_{g,i} > 1$. Therefore, the agent's estimates of the variance-covariance matrix of stock returns, denoted as $\widehat{\mathbf{\Omega}}$, are given by

$$\widehat{\mathbf{\Omega}} = \hat{\eta}_f^{-1}\tau_f^{-1}\boldsymbol{bb}' + \mathbf{\Sigma}_1, \qquad [4.6]$$

where $\mathbf{\Sigma}_1$ is a diagonal matrix with the $ii$th element given by $\hat{\eta}_{g,i}^{-1}\tau_{g,i}^{-1} > 0$. To have a direct correspondence with the CAPM, we rewrite the covariance matrix [4.6] as

$$\widehat{\mathbf{\Omega}} = \hat{\sigma}_m^2\widehat{\boldsymbol{\beta}}\widehat{\boldsymbol{\beta}}', \qquad [4.7]$$

[12] This (simplified) assumption reduces the number of parameters. Our results still hold if we alternatively consider the case that the signals are generally informative and the agents believes a higher precision (of the signals) than does an outside econometrician. This assumption also implies that the *ex ante* and the *ex post* distributions for the econometrician are the same.

[13] We can relax this assumption by assuming that the agent underestimates market volatility more heavily than individual stock volatilities on average, not necessary for each stock. In this case, the overconfidence relation ($c = \mathrm{x}'\Sigma\mathrm{x} > 0$) and our implications still hold as to be seen later. We acknowledge an anonymous referee for this helpful comment.

where $\widehat{\boldsymbol{\beta}}$ is an $N \times 1$ vector of the asset betas estimated by the agent with overconfidence, and $\hat{\sigma}_m^2$ is her *estimated* variance of the return of the market portfolio.

However, an outside econometrician with an unbiased belief knows that the signals are uninformative and that the true variance-covariance matrix is given by

$$\boldsymbol{\Omega} = \bar{\tau}_f^{-1}\boldsymbol{b}\boldsymbol{b}' + \boldsymbol{\Sigma}_2, \tag{4.8}$$

where $\boldsymbol{\Sigma}_2$ is a diagonal matrix with the $ii$th element given by $\bar{\tau}_{g,i}^{-1} > 0$.

Due to overconfidence, $\hat{\sigma}_m^2$ estimated by the agent is lower than the true market variance $\sigma_m^2$ estimated by the outside econometrician. Indeed, it follows from Equations [4.6] – [4.8] that the true variance-covariance matrix of the risky assets estimated by the outside econometrician who uses the true measure follows:

$$\boldsymbol{\Omega} = \sigma_m^2\widehat{\boldsymbol{\beta}}\widehat{\boldsymbol{\beta}}' - \boldsymbol{\Sigma}. \tag{4.9}$$

Therefore, the market volatilities under the two measures satisfy

$$\hat{\sigma}_m^2 = \frac{\sigma_m^2}{\hat{\eta}_f} < \sigma_m^2.$$

That is, the true volatilities are overly higher than those estimated by the irrational investor. In Eq. [4.9],

$$\boldsymbol{\Sigma} = \hat{\eta}_f\boldsymbol{\Sigma}_1 - \boldsymbol{\Sigma}_2$$

is a diagonal matrix with $ii$th element given by $\left(\frac{\hat{\eta}_f}{\hat{\eta}_{g,i}} - 1\right)\bar{\tau}_{g,i}^{-1} > 0$. It is consistent with the covariance matrix in the idiosyncratic volatility model of Stambaugh et al. (2015); however, we further provide a “microfoundation” of $\boldsymbol{\Sigma}$. Due to this factor, the agent underestimates market volatility more heavily than stock volatilities, consistent with Peng and Xiong (2006).[14] In all, overconfidence lowers $\hat{\sigma}_m^2$ while raises the diagonal elements of $\boldsymbol{\Sigma}$.

By definition, the assets’ market betas estimated by the econometrician satisfy

$$\boldsymbol{\beta} = \frac{\boldsymbol{\Omega}\mathbf{x}}{\mathbf{x}'\boldsymbol{\Omega}\mathbf{x}}, \tag{4.10}$$

where $\mathbf{x}$ is a $N \times 1$ vector of the weights in the market portfolio.

[14] This is termed *category-learning behaviour* in Peng and Xiong (2006).

By substituting Equation [4.9] into [4.10], and noting that $\mathbf{x}'\widehat{\boldsymbol{\beta}} = 1$, we obtain

$$\boldsymbol{\beta} = \frac{\sigma_m^2}{\sigma_m^2 - c}\widehat{\boldsymbol{\beta}} - \frac{\boldsymbol{\Sigma}\mathbf{x}}{\sigma_m^2 - c} \qquad [4.11]$$

where $c = \mathbf{x}'\boldsymbol{\Sigma}\mathbf{x} > 0$ and it increases with the degree of overconfidence. Equation [4.11] shows that the betas estimated by the agent ($\widehat{\boldsymbol{\beta}}$) are smaller than those ($\boldsymbol{\beta}$) estimated by an outside econometrician who knows the true parameters. In fact, overconfidence leads the agent to *underestimate* return correlations and hence shrinks the market betas.

In general, the mean return estimated by the agent could differ from that estimated by the outside econometrician. For simplicity, we assume that the agent has correct expectation for the asset returns. In other words, her expected returns of the risky assets, $\boldsymbol{\mu}$, are the same as those estimated by an outside econometrician. This conservative assumption also ensures that we do not mix the overconfidence impact with other behavioural mechanisms (*i.e.*, sentiment or lottery demand) that could influence the expected returns. Thus, our model generates the key insight that investor overconfidence alone could explain the time-series and cross-sectional patterns regarding the low-beta anomaly. Relaxing the assumption that the agent has correct expectations of asset returns will lead to richer results.

According to Sharpe (1964) and Lintner (1965), stock returns satisfy a CAPM relationship:

$$\boldsymbol{\mu} - r_f\mathbf{1} = \widehat{\boldsymbol{\beta}}(\mu_m - r_f), \qquad [4.12]$$

where $\mathbf{1}$ is a $N \times 1$ vector of ones, and $\mu_m$ is the expected return of the market portfolio. It follows from Equations [4.11] and [4.12] that

$$\boldsymbol{\mu} - r_f\mathbf{1} = \boldsymbol{\alpha} + \frac{\sigma_m^2 - c}{\sigma_m^2}(\mu_m - r_f)\boldsymbol{\beta}, \qquad [4.13]$$

where

$$\boldsymbol{\alpha} = \frac{\mu_m - r_f}{\sigma_m^2}\boldsymbol{\Sigma}\mathbf{x}. \qquad [4.14]$$

Equation [4.13] shows overconfidence decreases the slope of the SML by noting that $\frac{\sigma_m^2 - c}{\sigma_m^2} < 1$. The agent underestimates return correlations in equilibrium, leading the level of the betas estimated by the agent to be smaller than that estimated by an outside econometrician who knows the true parameters. In other words, the agent underestimates risks, especially for the high-risk firms. Therefore, the agent demands a lower risk-adjusted return on a high-beta stock than on a low-beta stock. Especially, sufficiently high degree of overconfidence ($c > \sigma_m^2$) can lead to a negative slope of the SML.

Therefore, we have the following proposition.[15]

**Proposition 1.1.** *An increase in the degree of the investor's overconfidence reduces the slope of the SML estimated by an outside econometrician. Sufficiently high degree of overconfidence leads to a negative slope of SML.*

Note equation [4.13] also indicates that CAPM does not hold under the econometrician's measure. In fact, the market portfolio is determined by the agent whose estimations of stock returns differ from those of the econometrician. As a result, although the market portfolio is efficient under the agent's measure, it can be inefficient under the econometrician's measure.[16]

An increase in the degree of overconfidence increases the diagonal elements of $\mathbf{\Sigma}$ and hence increases the risky assets' alpha in equation [4.14]. However, the slope of the SML in equation [4.13] decreases with overconfidence ($c$). In other words, overconfidence would have a strong impact on both the intercept and slope of the SML, but in completely *opposite* directions, which we test in the next section.

**Proposition 1.2.** *The slope of the SML estimated by an outside econometrician has a negative relationship with overconfidence, while the alphas have a positive relationship with overconfidence.*

Note that we study a full equilibrium model as the standard CAPM. In our model the CAPM equilibrium relationship holds under the subjective measure of the irrational agent who sets the equilibrium price, but the equilibrium could feature a negative slope of SML under the objective measure used by an outside econometrician who does not affect the equilibrium. The econometrician can access infinite data and hence know the true distributions. In contrast, the agent in standard CAPM

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[15] The condition $c > \sigma_m^2$ is equivalent to $\sum_i \left(\frac{\hat{\eta}_f}{\hat{\eta}_{g,i}} - 1\right) \bar{\tau}_{g,i}^{-1} x_i^2 > \sigma_m^2$. To estimate the condition, we consider a special case with all stocks having the same parameters ($\hat{\eta}_{g,i} = \hat{\eta}_g$ and $\bar{\tau}_{g,i}^{-1} = \bar{\tau}_g^{-1}$). In this case, the above inequality reduces to $\left(\frac{\hat{\eta}_f}{\hat{\eta}_g} - 1\right) \bar{\tau}_g^{-1} \sum_i x_i^2 > \sigma_m^2$. We set $\sigma_m^2 = 0.04$ (*i.e.*, an annualized market volatility of 20%), $\hat{\eta}_g = 1$ and $\bar{\tau}_g^{-1} = 0.25$ (corresponding to an annualized idiosyncratic volatility of 50% on average), and $\sum_i x_i^2 = 0.01$, which is the average value over our sample. Under the calibration, $c > \sigma_m^2$ leads to $\hat{\eta}_f^{-\frac{1}{2}} < 0.24$. By comparing [4.2] and [4.5], this means that to have a negative slope of SML the overconfident agent needs to underestimate market volatility by about three quarters. Note that for simplicity, our illustrative model does not feature other behavioural bias and constraints that help resolve the low-beta anomaly as documented in the literature. The interaction of overconfidence and these features should lead to a larger threshold for $\hat{\eta}_f^{-\frac{1}{2}}$.

[16] Roll (1977) and Ross (1977) question the efficiency of the market portfolio, and numerous empirical studies find that the market portfolio is indeed inefficient and typically far away from the efficient frontier (see, for example, Gibbons (1982), Jobson and Korkie (1982), Shanken (1985), Kandel and Stambaugh (1987), Gibbons et al. (1989), MacKinlay and Richardson (1991), and Jagannathan and Ma (2003), among others). Equation [4.13] is consistent with recent findings in Levy and Roll (2010), who show that slight variation in parameters may make an otherwise inefficient market portfolio efficient.

is rational and hence also play the role of the econometrician studied in our model. This is a major departure of our model from the CAPM.

We are aware that a number of behavioural mechanisms exist in the literature, which are able to explain the low-beta anomaly in the cross section.[17] We feel that the overconfidence mechanism is somehow being overlooked. In fact, our model with investor overconfidence is probably the most plausible in reconciling the stylized facts both in the cross-section and in the time-series dimensions. Other behavioural mechanisms such as investor sentiment or lottery demand are linked with the mean level of return (*i.e.*, mispricing) rather than volatility. Therefore, they cannot explain the time-series patterns including the negative sloped SML in China. Disagreement (*i.e.*, heterogeneous beliefs) alone also cannot explain the negative sloped SML, because the equilibrium price is a weighted average of different beliefs with wealth-dependent weights. As such, our model of overconfidence complements existing theories of the low-beta anomaly by also exploring return volatilities.

Furthermore, it should be noted that the downward-sloping SML cannot be easily reconciled with the extant theories that usually attribute the beta anomaly to some sorts of constraints, such as the borrowing constraints (Black 1972), leverage and margin constraints (Frazzini & Pedersen 2014), and short-sales constraints (Liu et al. 2018). Intuitively, constraints may "flattened" the SML, but cannot flip the "sign" of the slope of the SML (Black 1972; Jylha 2018). As shown later (in **Section 6**), the profits of the BAB strategy stem mainly from the long leg of the portfolio in China. This is opposite to the predictions of short-sale constraints that, interacting with sentiment, cause the beta anomaly to originate from the short legs as demonstrated in Stambaugh et al. (2015) and Liu et al. (2018). Apparently, other economic force(s) must be in play. Our behavioral model, however, can reconcile the observed downward-sloping SML in China.

## 5. Time-series Evidence

### 5.1. Investor Overconfidence and Trading Volume

While overconfidence is not directly observable, prior literature focuses on the behaviour of overconfident investors has establish a strong positive link between trading volume and investor overconfidence (Statman et al. 2006; Daniel & Hirshleifer 2015). For example, Odean (1999)

[17] While the novelty of our model lies mainly at the time-series dimension, it could also generate the low-beta anomaly in the cross section. This follows directly from equations [4.11] and [4.14] that $\boldsymbol{\alpha} = \frac{\mu_m - r_f}{\sigma_m^2}\left[\sigma_m^2 \widehat{\boldsymbol{\beta}} - (\sigma_m^2 - c)\boldsymbol{\beta}\right]$. Therefore, investor overconfidence leads to the beta anomaly, as the alpha of the risky assets *decreases* in the beta for $\sigma_m^2 - c$.

documents that overconfident investors trade too much, and they tend to hold a larger position in risky assets than rational investors, because they (falsely) believe they have private information. Barber and Odean (2000, 2001) find similar evidence that the portfolios of overconfident investors exhibit higher portfolio turnover and greater risk. At the aggregated level, Statman et al. (2006) utilize market-wide turnover as a direct measure of investor overconfidence, and find that the degree of investor overconfidence varies positively with (lagged) market returns over time. That is, the intertemporal changes in the degree of overconfidence are induced by biased self-attribution in investors that experience high market outcomes, even when those returns are simultaneously enjoyed by the overall market (Gervais & Odean 2001; Ben-David *et al.* 2013; Ben-David *et al.* 2018).

Motivated by these findings and consistent with our theoretical model, we employ market-wide turnover ratio as the proxy of overconfidence. Intuitively, an increase in the degree of overconfidence decreases return volatilities estimated by the representative agent and hence increases her total demand and trading volume (because trading volume decreases with volatilities in the mean-variance framework of CAPM).[18]

We are aware that the time variations of the aggregated turnover could also be driven by other factors, such as market volatility, liquidity, and economic uncertainty. Therefore, in our time-series tests (in the next subsection) we control for other possible economic mechanism(s) to ensure that the observed net effect of market trading volume better reflects investor overconfidence.

### 5.2. The Empirical Model

To test the time-series predictions of our theoretical model, we follow the standard two-step procedure to test the determinants of the SML (Jylha 2018). In the first step, we perform the month-by-month Fama-MacBeth cross-sectional regression (as in **Section 3**) by regressing the excess returns of the beta-sorted decile portfolios on their CAPM betas to obtain the time series of the intercept and slope of the SML.

[18] For parsimony, we study a one-period model, in which trading volume cannot be defined. However, it can be extended to a dynamic one with multiple agents to define the trading volume, even though the extended model would be much more complicated and beyond our scope. For example, Chiarella et al. (2013) study a dynamic model with multiple assets and many agents who have different preferences and different beliefs about the expected returns and variance-covariance matrices. Both population fractions and agents' beliefs are endogenously determined. They show that the trading volume defined as the sum of the absolute value of the change in agents' demands is inversely proportional to one agent's variance-covariance matrix with two types of two agents. Because overconfidence in our model proportionally reduces the variance-covariance matrix, trading volume should increase with overconfidence.

$$Ret_{it} - RF_t = Intercept_t + Slope_t \beta_{it} + \varepsilon_{it} \quad [5.1]$$

This provides us with the dependent variables used in the second-step time-series regression. According to Jylha (2018), the intercept and slope of the SML represent a zero-cost zero-beta portfolio and a zero-cost unit-beta portfolio, respectively. In the second step, we regress the time series of the intercept and slope coefficients on the lagged market-wide turnover ratio, our proxy for investor overconfidence. The monthly turnover ratio (denoted as $TURN$) is constructed as the value-weighted average across all firms in the market.

$$Intercept_t = a_1 + b_1 TURN_{t-1} + \boldsymbol{c}_1' \boldsymbol{X}_t + u_{1,t} \quad [5.2]$$

and

$$Slope_t = a_2 + b_2 TURN_{t-1} + \boldsymbol{c}_2' \boldsymbol{X}_t + u_{2,t} \quad [5.3]$$

To ensure that the observed net effect of market turnover reflects mainly the impact due to investor overconfidence, we control for other possible economic mechanisms that could lead to the intertemporal changes in trading volume such as lagged market volatility, liquidity, and economic uncertainty. The lagged market volatility ($Sigma$) is defined as the standard deviation of the daily market returns within the prior month. The lagged market liquidity ($ILLIQ$) is proxied by the value-weighted average of the Corwin and Schultz (2012) implied spread measure. To purge the rational response of trading volume to the shifts in market conditions, we also include the lagged economic policy uncertainty index ($EPU$) for China, obtained from Baker et al. (2016), to control for the time variation of the market-wide economic uncertainty. We also include lagged return dispersion ($DISP$), defined as the monthly cross-sectional standard deviation of returns, as an additional control to account for possible trading activities associated with portfolio rebalancing. Following Jylha (2018), we also include a number of contemporaneous risk factors: the Fama-French five factors, Carhart's momentum factor, and the short-term reversal factor.

### 5.3. The Time Variation of the Shape of the SML

**Table 2** provides the estimation results for the second-stage time-series regression of the intercept and slope of the SML. To facilitate comparison, we have standardized the market turnover ratio, the market volatility, the market liquidity, the EPU measure, and the return dispersion measure (*i.e.*, zero mean and unit variation) before putting them into the regression model. A number of salient features emerge from the table:

First, the most striking finding of the table is that trading volume (*i.e.*, market-wide turnover ratio) does have a superior impact on the time variation of both the intercept and the slope of the SML in China, after accounting for all other control variables (columns 1 to 6). Given that we have accounted for other possible mechanisms that could lead to the intertemporal changes in trading volume (by including market volatility, liquidity, economic uncertainty, and cross-sectional return dispersion), the loadings on turnover ratio lend strong supports to **Propositions 1.1 and 1.2**. That is, an increase in the degree of the investor's overconfidence, proxied by the market-wide turnover ratio, reduces the slope of the SML. Moreover, the opposite signs of the loadings on turnover ratio for the zero-beta portfolio and the unit-beta portfolio confirm that shifts in investor overconfidence would impact the intercept and slope of the SML in exact opposite directions. To be specific, following high market-wide trading volume, the slope of the SML becomes more downward-sloping while the intercept term of the SML would adjust upwards, indicating a stronger mispricing in the cross section (*i.e.*, low-beta stocks outperform high-beta ones). In other words, after accounting for other economic mechanisms, the low-beta anomaly becomes more pronounced in response to the increase of (lagged) trading volume.

Second, the economic significance of the loadings on the lagged turnover ratio is also impressive, a one-standard-deviation shock in turnover ratio would lead to a downward adjustment of 1.84% percent for the zero-cost unit-beta portfolio (*i.e.*, the slope of the SML), and an upward adjustment of 2.05% percent for the zero-cost zero-beta portfolio (*i.e.*, the intercept of the SML). In comparison, although the signs of factor loadings on these alternative economic mechanisms (*i.e.*, market volatility, liquidity, economic uncertainty, and return dispersion) are in general as expected, none of these factor loadings are statistically different from zero. Moreover, the economic consequences for a one-standard-deviation shock in market volatility, liquidity, economic uncertainty, and return dispersion are relatively small as compared to those of the turnover ratio. Therefore, from the economic perspective, it seems that trading volume is a much stronger time-series determinant of the low-beta anomaly than the other competing mechanisms in China.

[**Insert Table 2 here**]

### 5.4. Investor Overconfidence and Biased Self-Attribution

It is well-established in the behavioural literature that biased self-attribution causes the degree of overconfidence to vary with realized market outcomes (Gervais & Odean 2001; Ben-David *et al.* 2013; Ben-David *et al.* 2018). That is, overconfident investors tend to attribute good outcomes to their own skills and bad outcomes to external reasons such as bad luck (*i.e.*, self-attribution bias). Given the interaction between overconfidence and biased self-attribution (as the representative agent "confuses brain with a bull market"), we have good reasons to believe that the SML will become more inverted when investors get more overconfidence in bull markets, even though these high market returns are simultaneously enjoyed by all market participants.[19]

To capture this possible *dynamic* overconfidence effect, we use the prior market performance as the proxy for self-attribution bias. To be specific, we generate a dummy variable ($MS$) which equals one when the prior 6-month cumulative market return is positive and zero otherwise. The dummy variable captures the psychological tendency that investors attribute good market performance to their own skills (*i.e.*, self-attribution bias).[20] We then augment our empirical model in Equations [5.2] and [5.3] with the $MS$ term and its interaction term with the turnover ratio. For robustness and also to ensure that self-attribution bias might be more prominent the larger the magnitude of the prior market outcomes, we use the magnitude of average market return over the prior 6 months (*i.e.*, a continuous variable) to interact with turnover ratio as an alternative model specification. The dummy term facilitates easy interpretation on whether the SML becomes more inverted when the market is doing well, while the interaction term captures the *asymmetric* overconfidence effect induced by self-attribution bias.

**Table A3** in the appendix provides the estimation results. Column 1 reproduces the unconditional pattern with no dummy and interaction terms (which is the same as column 6 in **Table 2**). Column 2 reports the augmented model with the $MS$ term and its interaction term with the turnover ratio. As expected, the loadings on the $MS$ dummy is highly positive for the intercept of the SML and highly negative for the slope of the SML, indicating that the SML, on average, is highly inverted in good times (*i.e.*, high overconfidence) relative to bad times (*i.e.*, low overconfidence). This striking conditional pattern that the SML is highly inverted in bull market provides strong supports to **Proposition 1.1** that sufficiently high degree of overconfidence leads to a negative slope of SML.

Coefficients on the interaction terms between market turnover and the $MS$ dummy confirm the *dynamic* overconfidence effect: When investors get more overconfident due to biased self-attribution, market-wide turnover ratio exerts (additional) downward predictability for the zero-cost unit-beta portfolio (*i.e.*, the slope of the SML) and upward predictability for the zero-cost zero-beta portfolio

[19] We are highly indebted to Annette Vissing-Jorgensen for directing us to test this asymmetric pattern, which helps differentiate our overconfidence mechanism from alternative mechanisms such as over-extrapolation.

[20] The 6-month "looking back" period is inconsequential, as we find qualitatively similar results when using alternative 3-month, 9-month, and 12-month "looking back" period to define the dummy variable ($MS$).

(*i.e.*, the intercept of the SML), reinforcing our overconfidence-based mechanism. The fact that coefficients on market turnover for both the intercept and slope of the SML become insignificant once we include the $MS$ term and its interaction term with market turnover yields additional insights. That is, the overconfidence effect on the SML is highly *asymmetric*, because it mainly concentrates in bull markets when investors are plagued with the symptoms of enhanced self-attribution bias.

Column 3 reports the results of the alternative model specification in which we use the continuous variable, the magnitude of average market return over the prior 6 months, to interact with market turnover. The coefficients on the interaction term are highly significant with the predicted signs for both the intercept and slope of the SML, indicating that the overconfidence-based mechanism is indeed more prominent the larger the magnitude of the prior market outcomes.

To sum up, when interpreting the results from **Table 2** and **Table A3** collectively, the impact of investor overconfidence on the SML becomes clear: Subsequent to heightened investor overconfidence, manifested by excessive trading volume, relatively risky assets (*i.e.*, high-beta stocks) underperform relatively safe assets (*i.e.*, low-beta stocks), implying a more "inverted" SML. In other words, the price of risk becomes more negative subsequent to excessive trading volume.

## 6. Cross-sectional Evidence

### 6.1. Betting Against Beta

Motivated by the "flattened" CAPM line in the US, Frazzini and Pedersen (2014) designed a market-neutral BAB strategy, which takes a leveraged long position in low-beta stocks and a deleveraged short position in high-beta stocks to "capitalize" on the low-beta anomaly. Intuitively, the "inverted" SML in China should lead to a more profitable BAB portfolio. Therefore, we test directly the profitability of the BAB strategy in China.

Following Frazzini and Pedersen (2014), the BAB portfolio is constructed in three steps:

First, at the beginning of each month, all stocks are ranked in ascending orders by their *ex ante* market beta based on a rolling window of the prior five-year daily data. All stocks with a beta value below (above) the cross-sectional median are assigned to the low (high) beta portfolios. Note the market beta is defined in the same manner as in Frazzini and Pedersen (2014), which is the product of a stock's return correlation (with the market portfolio) and the market-adjusted volatility (see **Appendix A.1** for variable definitions).

Second, the portfolio weights of the composite stocks are determined by their rankings of beta: Relatively lower (higher) beta stocks in the low (high) beta portfolio are given higher (lower) portfolio weights. Analytically, the rank-based weighting scheme for the low (high) beta portfolio is expressed as follows:

$$w_{L(H)} = k(z - \bar{z})^{-(+)} \qquad [5.4]$$

where $k = 2(\mathbf{1}_n'|z - \bar{z}|)^{-1}$ is the normalizing factor, $z$ is the $n \times 1$ vector of beta ranks with the elements of $z_i = rank(\beta_i)$, $\bar{z}$ is the $n \times 1$ vector with each element equals the cross-sectional mean of the beta ranks, and $x^{-(+)}$ denotes the negative (positive) elements of the $n \times 1$ vector $x$.

Third, using the beta-parity approach, both the low beta portfolio (*i.e.*, the long-leg) and the high beta portfolio (*i.e.*, the short-leg) are rescaled to produce an *ex ante* unit portfolio beta at the portfolio formation. That is, the long leg (short leg) is scaled up (down) by leveraging (deleveraging) its position. In this way, the BAB portfolio becomes a self-financing, long-and-short portfolio which has an *ex ante* beta of zero.

$$BAB = \frac{1}{\beta_L} R^{LOW} - \frac{1}{\beta_H} R^{HIGH} \qquad [5.5]$$

where $R^{LOW} = r'w_L$, $R^{HIGH} = r'w_H$, $\beta_L = \beta' w_L$, $\beta_H = \beta' w_H$, and $r$ is the vector of excess returns over risk-free rate. We have dropped the time subscript in the above expression for concise purposes.

**Table 3** presents the sample statistics on the BAB strategy in China. On average, the BAB strategy delivers an impressive monthly return of 0.99 percentage, with a standard deviation of 3.46 percentages per month. The annualized Sharpe ratio has a value of 0.99 during the sample period between July 1996 and December 2016 (*i.e.*, 246 months). The (unlevered) long leg of the BAB strategy, the low beta portfolio, has an average excess return of 1.96 percentages per month with an annualized Sharpe ratio of 0.72. In comparison, the unlevered short leg of the BAB strategy, the high beta portfolio, earns an average excess return of 1.32 percentages per month with an annualized Sharpe ratio of 0.42. The large differentials in monthly return and the Sharpe ratio between the long leg and the short leg again reinforce the strong low beta effect in China. The historical average of the *ex ante* betas for the low and high beta portfolios are 0.92 and 1.21, which translates into a scaling factor of 1.087 and 0.826 in leveraging the long leg and deleveraging the short leg, respectively.

To evaluate the BAB strategy, however, requires a bit of decision making in choosing the proper performance benchmark. The strong low-beta anomaly detected in the earlier study (Frazzini & Pedersen 2014; Schneider et al. 2015) might be partially due to the incapacity of the CAPM and the

Fama-French three factor models in explaining the time variation of portfolio returns. Therefore, we use mainly the Fama-French five factor model to adjust the risk exposure of the BAB portfolio and its associated long and short legs.

The latter few columns in **Table 3** report the regression output with the Fama-French five-factor model. The BAB portfolio loads positively on the market factor and negatively on the value factor over the entire periods. After accounting for the risk exposure, the BAB portfolio achieves a risk-adjusted return of 0.80 percent per month, which is significant at the 1% level. The superior risk-adjusted performance of the BAB strategy is consistent with the “downward-sloping” SML found at the firm-level in China, implying that low-beta stocks outperform high-beta stocks on a risk-adjusted basis.

A separate examination on the excess returns (over risk-free rate) of the (unlevered) long leg and short leg of the BAB strategy yields more insights regarding the sources of the profitability. The profits mainly stem from the long leg of the BAB portfolio as the low beta portfolio earns a monthly alpha of 0.68 percent on average, which is significant at the 1% level. In contrast, there is little evidence that high-beta stocks underperform, as the associated alpha is insignificant from zero (*t*-stat. = -0.52). The fact that the profits of the BAB strategy in China stems mainly from the long leg has strong practical implications. It means that the low beta strategy is exploitable even for those long-only investors such as pension funds and small retail investors. Those investors are constrained in taking short positions due to either mandate or the high costs related to shorting.

[**Insert Table 3 here**]

To generate more insights, we replicate the exercise for the US stocks over the same sample period (see **Table A2** in appendix). In comparison, the BAB strategy in the US also provides superior performances as it generates an average return of 0.83 percent with a standard deviation of 4.38 percent per month. The annualized Sharpe ratio is 0.66 over the sample period from July 1996 to December 2016 (*i.e.*, 246 months). It is much smaller than the counterpart in China (0.99), confirming that the “inverted” SML in China generates much greater investment opportunity than in the US. The long leg (low beta portfolio) has an average monthly return of 1.17 percent which is comparable to the 1.14 percent generated by the short leg (high beta portfolio). The annualized Sharpe ratios are 1.07 and 0.44 for the long and short legs, respectively. The historical average of the *ex ante* portfolio betas for the low and high beta portfolios are 0.63 and 1.33, which imply a relatively larger leverage/deleverage position for the BAB strategy in the US compared to China.

After accounting for the risk, the BAB portfolio in the US achieves an alpha of 0.49 percent per month, which is not statistically significant and is also much smaller than the counterpart in China (0.80). Similar to the patterns in China, the profits of the BAB strategy in the US also stems mainly from the long leg of the portfolio that has an alpha of 43 basis points per month with a *t*-statistics of 2.31. There is, however, no evidence of underperformance in the short leg as its alpha is positive but statistically insignificant.[21]

### 6.2. Time-series Spanning Tests

In the prior subsection, it is noted that the BAB strategy in China generates significant alphas when accounting for the Fama-French five factors. As these time-series regressions can be interpreted as the spanning tests on the BAB strategy, they further confirm that the pricing power of the BAB strategy is not fully subsumed by the traditional trading strategies (*i.e.*, the explanatory strategies) such as the market, size, and value strategies.

This subsection then treats the BAB-type portfolios directly as the explanatory strategy and uses it to test the traditional trading strategies (*i.e.*, the test strategies). The traditional *market*, *size*, *value*, *profitability*, and *investment* strategies are proxied by the Fama-French five factors (*i.e.*, RMRF, SMB, HML, RMW, and CMA). In general, significant abnormal returns would suggest an investor already trading the explanatory strategies could realize significant gains by starting to trade the test strategy. Insignificant abnormal returns would, however, suggest that he or she has little to gain by starting to trade the test strategy.

It should be noted that the original BAB portfolio requires the usage of margin to lever up the long leg and deleverage the short leg, which results into an overall net-long position of the risky assets (Han 2019). However, traditional risk factors are *pure* long-and-short portfolios (*i.e.*, a zero-cost position).

[21] We are aware the critiques by Novy-Marx and Velikov (2018) on the non-conventional portfolio construction techniques used in BAB, such as the rank-based weighting scheme and hedging by leverage, which amplifying the overall performance of BAB by increasing the exposure to small-cap firms. To alleviate the size concern, we follow Han (2019)'s non-parametric decomposition framework to partition the total (risk-adjusted) return of BAB into the components due to the stock selection ability (*i.e.*, pure low-beta strategy), the rank-based weighting scheme, and the beta-parity approach (*i.e.*, due to leverage), respectively. The decomposition results suggest that the majority of the superior (risk-adjusted) performance of BAB in China stems from the stock selection component (*i.e.*, the pure low-beta strategy), while the beta-parity component is key driver of the outperformance of BAB in the US (Results are available upon request). Therefore, our key results in China are insensitive to the usage of rank-based weighting scheme or the hedging by leverage approach. We thank the two anonymous referees for the suggestion.

Therefore, to make a fair comparison, we use the unlevered rank-weighted BAB or equally-weighted BAB portfolios as the alternative proxies for the BAB strategy.

Panel A of **Table 4** reports the results using the unlevered rank-weighted BAB portfolio as the explanatory strategy. The intercepts for the profitability, and investment factors become insignificant, indicating the profits of these two strategies are subsumed by the BAB strategy (*i.e.*, low beta strategy). In comparison, the intercepts for the market, size, and value strategies remain statistically significant at 5% or finer level, indicating that the time-variation of these three test strategies are not subsumed by the BAB strategies. The fact that the market strategy is not subsumed by the unlevered rank-weighted BAB portfolio is understandable, because the BAB-type strategy is a long-and-short strategy by construction, which should not capture the time variation of the long-only market portfolio.[22]

Similarly, panel B of **Table 4** present the results with the unlevered equally-weighted low-minus-high beta portfolio (*i.e.*, the first "benchmark" portfolio in the performance attribution framework) as the explanatory strategy. In general, the explanatory power for this low-minus-high beta portfolio is quite similar to its rank-weighted version. The intercepts for the market, size, and value strategies remain significant, while those for the profitability and investment strategies are still insignificant.

[**Insert Table 4 here**]

Overall, it is fair to state that the BAB-type factor exhibits strong power in explaining (partially) the time-variation of the RMW and CMA factors. That is, the explanatory power of these two unlevered BAB (low-minus-high beta) testing strategies is particularly impressive as the adjusted $R^2$ is 25.2% (27.4%) and 16.2% (17.2%) for the RMW and CMA factors.

### 6.3. Univariate Portfolio Sorts and Stock Characteristics in China

The Frazzini and Pedersen (2014) BAB strategy involves buying half of the securities (low-beta stocks) and selling the other half (high-beta stocks) within the entire market, and utilizes the active rank-based weighting scheme and leveraging/deleveraging tools. These "active" tweaks help amplify the return differentials between low-beta and high-beta stocks. However, an alternative portfolio strategy to capture the beta effect would be to focus on the lowest and the highest beta stocks. Therefore, in this subsection, we follow the traditional asset pricing logic by forming the equally-

[22] In unreported analysis, we find that the original BAB portfolio subsumes the market strategy as the intercept for the market strategy is indifferent from zero.

weighted beta-sorted decile portfolios to dissect the low-beta anomaly in China. That is, at the beginning of each month, all available stocks are assigned to ten groups based on their market beta in ascending orders.

[**Insert Table 5 here**]

**Table 5** reports the average firm characteristics of the composite stocks within each of the beta-sorted decile portfolios. All reported statistics are first computed as the equal-weighted average of all the composites in the decile portfolios, and then averaged across the entire sample periods (*i.e.*, 246 months). The average beta ranges from 0.82 in the low beta portfolio (decile 1) to 1.29 in the high beta portfolio (decile 10). Moving across the table, it seems that low beta portfolios have higher excess returns than high beta portfolios, a pattern that is consistent with the "inverted" CAPM documented in **Section 3**. There are, on average, around 118 composite stocks within each decile portfolios.[23]

Conventional wisdom tends to assume that high-beta stocks are small-cap stocks. This view, however, is not fully supported by the data: While the lowest beta portfolio seems to be dominated by large-cap stocks, the average size of the highest beta portfolio is ranked fourth among all the decile portfolios. That is, at least some of the highest beta stocks are from the large-cap or medium-cap firms. The non-monotonic relation also applies to the book-to-market equity. Interestingly, the lowest beta decile is dominated by growth stocks with the low book-to-market ratios. The highest beta decile, however, has firms with medium level of book-to-market ratios.

There does exist, however, a monotonic pattern in terms of the operational profitability and the growth rate of total assets. That is, low-beta stocks tend to be the firms with higher operational profits and relatively higher growth rate in total assets.

There is also no monotonic pattern for the intermediate-term return momentum except that the highest beta decile portfolio seems to be dominated by winner stocks (over the prior year). On the other hand, the highest beta decile portfolio tends to invest in stocks that have the best performance over the prior month, which might lead to strong return reversal over a short period.

When examining other popular risk measures or behavioural features. There does exist a number of monotonic patterns. In general, low-beta stocks have relatively high values in coskewness (SSKEW), and price level (PRICE). They also have relatively low values in idiosyncratic skewness (ISKEW), idiosyncratic volatility (IVOL), maximum daily returns in prior month (MAX5), prior one-month

[23] The total number of available stocks growth steadily over time from 263 stocks in July 1996 to 2,345 stocks in December 2016 owing to the rapid growth of the Chinese stock markets over the recent decades.

return ($\mathrm{RET}^{\mathrm{STREV}}$), and average turnover ratio (TURN). On the contrary, high-beta stocks tend to have low values in coskewness (SSKEW), and price level (PRC), while high values in idiosyncratic skewness (ISKEW), idiosyncratic volatility (IVOL), maximum daily returns in prior month (MAX5), prior one-month return ($\mathrm{RET}^{\mathrm{STREV}}$), and average turnover ratio (TURN).

### 6.4. Performance Evaluation of the Beta-sorted Decile Portfolios

In this subsection, we examine the performance of the beta-sorted decile portfolio over the sample periods. The first row of **Table 6** presents the average excess return of the decile portfolios. Consistent with the downward-sloping CAPM line documented in **Section 3**, we find a monotonically decreasing pattern: the high the stock beta, the lower the portfolio returns. A careful look at the (annualized) Sharpe ratios provides more direct evidence of the low beta effect: The low beta portfolios tend to outperform the high beta counterparts from a pure mean-variance investor's perspective.

The next few lines of the table report the portfolio performance on a risk-adjusted basis. For robustness purpose, we have tested the performance of these decile portfolios under a variety of factor models, including the CAPM, the Fama-French three-factor, the Fama-French five-factor models, and the Fama-French five-factor model augmented with the Carhart (1997) momentum and short-term reversal factors (denoted as **FF7**). Following the methodology of Daniel et al. (1997), we also calculate the DGTW characteristics-adjusted returns for each decile portfolio.

Our results are compelling. No matter which factor model is used, there exists a monotonically decreasing pattern of portfolio alphas from decile one to decile ten. That is, after adjusting for the risk exposure (i.e., RMRF, SMB, HML, RMW, CMA, MOM, STREV), low-beta stocks tend to have higher risk adjusted returns, while high-beta stocks have lower risk adjusted returns. The return differential between low beta and high-beta stocks is also strikingly large on a risk-adjusted basis, which confirms the low-beta anomaly documented in the literature (Frazzini & Pedersen 2014). For example, the zero-cost, high-minus-low beta portfolio, which goes long the decile ten portfolio and short the decile one portfolio, produces a negative Fama-French five-factor alpha of -1.38 percentages per month, which is statistically significant at the 1% level.

In general, the outperformance of the low-beta stocks is highly consistent. Moving across the alternative asset pricing models, the alphas of the lowest beta decile remain statistically significant in all cases. On the other hand, we do not find consistent evidence for the underperformance of the highest beta decile. The risk-adjusted returns for the highest beta decile are significantly negative when evaluated by the Fama-French three-factor model, the augmented seven-factor model, and the DGTW characteristics-adjustments, but are indifferent from zero when evaluated with the CAPM and the Fama-French five factor models.

[**Insert Table 6 here**]

## 7. Further Analyses and Robustness Tests

### 7.1. The "Horse Race"

Multiple competing, risk-based or behavioural explanations have been extended by researchers to explain the pervasive low-beta anomaly in the financial markets (Baker et al. 2011; Frazzini & Pedersen 2014; Schneider et al. 2015; Bali et al. 2017; Liu et al. 2018). Moreover, we also find a number of monotonic patterns in firm characteristics associated with the beta-sorted portfolios in **Section 6.3**. However, focusing on the portfolio-level evidence makes it difficult to draw strong conclusions regarding the driver of the low-beta anomaly for a number of reasons. First, the aggregation to the portfolio level might "overlook" important firm-level cross-sectional information and do not increase the precision of the coefficient estimates (Ang et al. 2008). Second, the aggregation might inflate the correlation between firm characteristics and the test variable (Hou & Loh 2016). Third, the pricing pattern of the test variable (*i.e.*, beta) might stem from the "residual" part that is orthogonal to the firm characteristic, a possibility that is cautioned by Hou and Loh (2016).

To circumvent the above caveats, we adopt the novel firm-level decomposition approach proposed in Hou and Loh (2016) to evaluate the competing explanations on the low-beta anomaly. Following Hou and Loh (2016), we use the DGTW characteristics-adjusted returns as the dependent variable for the decomposition exercise. The Hou and Loh (2016) decomposition exercise proceeds in three stages (A detailed walk-through of the decomposition exercise is available in **Appendix A.2**): In the first stage, the univariate Fama-MacBeth cross-sectional regressions are performed by regressing the characteristics-adjusted returns on market betas to obtain the time series of the slope coefficients on betas, $\hat{\lambda}_t$. In the second stage, an orthogonalization regression is performed for each month to decompose the market beta into two components: one that is explained by the (sole) candidate variable $Z$, the other that is the unexplained part (the intercept plus the residual term). That is, the beta of an individual stock is the sum of the explained component and the unexplained component. In the final stage, the average beta coefficient obtained in the first stage is further decomposed into two orthogonal components based on the property of linearity of covariance. That is, the explained and the unexplained coefficients (*i.e.*, $\overline{\hat{\lambda}(Z)_t^{Explained}}$ and $\overline{\hat{\lambda}_t^{Unexplained}}$) sum up to the time-series average of the slope coefficient $\overline{\hat{\lambda}_t}$, making it easy to quantify the pure contribution of the candidate variable $Z$ in explaining the negative beta-return relation. The above decomposition exercise is repeated for a number of candidate variables, providing a "horse race" to objectively compare the ability of each candidate variable in explaining the observed beta-return relation in China.

**Table 7** reports the results of the "horse race". The first column examines the operational profitability measure (OP) in explaining the low-beta anomaly. Novy-Marx (2013) argue that investors demand higher returns for firms with higher profitability. For operational profitability (OP) to explain the beta anomaly, we need to ensure that low (high) beta stocks are associated with high (low) operational profitability, a pattern that is consistent with our findings in **Table 6**. However, after decomposing the slope coefficient on beta into the explained and unexplained portions, we find that the explained portion due to OP explains virtually zero percent of the low-beta anomaly. It seems that the low-beta anomaly is driven purely by the part that is orthogonal to the operational profitability of a firm. The disconnection between the portfolio-level evidence (**Table 6**) and the firm-level evidence (**Table 7**) reinforces the point cautioned in Hou and Loh (2016) that the pricing power of the test variable (*i.e.*, beta) might stems entirely from the residual part that is unrelated to the (correlated) firm characteristic. Similarly, we find no evidence for firm investment (INV) to be the driver of the low-beta anomaly, as the decomposition exercise demonstrates that the "explained" slope coefficient is 0.05 and the explained portion is -4% and not statistically significant (see column 2).

The possibility that high-beta stocks are also the stocks with the highest returns in the prior month, which leads to lower returns in the subsequent month, seems to receive some support as in **Table 6**. However, this conjecture does not receive much support in the decomposition exercise. The explained proportion due to prior one-month return ($\text{RET}^{\text{STREV}}$) is only around 4%, and it is not statistically significant. The low-beta anomaly is driven by the part that is orthogonal to the short-term return reversal measure (see column 3). In other words, the short-term reversal effect is not a viable solution to the low-beta anomaly.

The fourth column evaluates the lottery demand measure, MAX5, as the candidate variable in explaining the low-beta anomaly. Based on portfolio sorts, Bali et al. (2017) provides a lottery demand explanation on the beta anomaly in the US. We find similar pattern at portfolio level in China as low-beta stocks are with low MAX5 values, while high-beta stocks tend to have high MAX5 measures (**Table 6**). The result from the decomposition exercise re-confirmed its strong power in explaining the low-beta anomaly, as the explained proportion due to MAX5 amounts to 98%, which is statistically significant at the 1% level.

The fifth column evaluates the Harvey and Siddique (2000) coskewness measure (SSKEW). As a risk measure, a stock with a high coskewness value would offer insurance for the investors when market volatility increases (Harvey & Siddique 2000). Thus, investors who have a strong preference for high coskewed stocks are willing to pay a higher price to hold them. Based on a two-factor pricing kernel that includes the squared market returns, Schneider et al. (2015) show that the CAPM beta, which ignores the coskewness effect on asset price, systematically overestimates the risk of high-beta stocks. However, this rational justification does not find strong support in our dataset, because high-beta stocks tend to have more negative values of the coskewness measure in **Table 6** (*i.e.*, the more negative the coskewness measure, the higher the required returns of these stocks). If coskewness is the main reason in explaining the beta anomaly, we would expect the exact opposite patterns for coskewness in the beta-sorted decile portfolio. The decomposition exercise also points to the direction that the coskewness-based view cannot explain the low-beta anomaly, because the explained portion by the coskewness measure is -3.0%.

The next column evaluates the idiosyncratic skewness (ISKEW). As a candidate variable for the lottery-demand explanation, Barberis and Huang (2008) argue that investors are willing to pay for stock with negative payoffs but offering a slight possibility of dramatic upside potentials. In other words, investors are willing to overpay stocks with positive skewed return distribution. This skewness-based explanation, however, does not yield much power in explaining the return-beta pattern, because the idiosyncratic-related component only contributes to 4% of the negative slope coefficient on betas, and this proportion is statistically insignificant.

The next candidate variable is the Ang et al. (2006) idiosyncratic volatility (IVOL) measure (see column 7). Liu et al. (2018) provide a short-sales constraints-based explanation of the beta anomaly. They argue that due to the "guilty" association with idiosyncratic volatility, high-beta stocks offer low average returns. Both the portfolio-level evidence (**Table 6**) and the decomposition exercise provide consistent evidence: The idiosyncratic volatility measure does explain a substantial part of the inverse return-beta relation. The relative proportion explained by the idiosyncratic volatility measure amounts to 83%, which is significant at the 5% level.[24]

[24] It should be noted that the strong explaining power from idiosyncratic volatility and MAX5 in explaining the beta anomaly might simply be mechanical. By construction, beta is a measure of risk that is highly correlated with a stock's

Column 8 evaluates the price level (PRC). Lower priced stocks are generally perceived by naïve investors as the "typical" lottery-type stocks, which seem to have unlimited upside potentials. This makes the price level as another proxy for the lottery demand in the sense of Bali et al. (2017). That is, lottery investors are willing to *overpay* the low-priced stocks (high-beta stocks) for a small chance of unlimited reward. In general, higher beta portfolios tend to have more low-priced stocks as is indicated in **Table 6**. However, the price level does not explain the inverse relation between returns and market beta, because the explained portion by the price level is approximately -9.0% and it is insignificant as well in the decomposition exercise.

Last but not least, we evaluate the firm-level turnover ratio (TURN) in explaining the low beta effect. Consistent with our conjecture in Section 4 and 5, we treat turnover ratio as a "catch-all" behavioural variable for investor overconfidence. In the behavioural literature, overconfidence induces excessive trading volume in speculative assets (Scheinkman & Xiong 2003). Moreover, higher-volume stocks receive more investor attention in the cross section, a symptom of investor overconfidence or overreaction (Baker et al. 2011). Higher-volume stocks also enjoy greater price disagreement (Miller 1977) and are, in general, difficult to arbitrage (Chou et al. 2013). Note extremely high turnover ratio could also (partially) reflect high lottery demand, because retail investors engage in correlated trading for these stocks (Kumar & Lee 2006). All of the above behavioural mechanisms dictate that stocks with high turnover ratio (high-beta stocks) are likely to have low subsequent returns, as a symptom of investor overconfidence. In **Table 6**, there does exist a monotonic pattern between stock betas and the turnover ratio, as the average turnover ratio increases along with the stock beta of the decile portfolio. The decomposition results reinforce our conjecture. The explained proportion by TURN amounts to 122%, which is statistically significant at the 5% level. In other words, the beta pricing pattern is almost completely captured by the turnover ratio.[25] We are aware that some might argue that high-volume stocks tend to have low expected returns for rational or quasi-rational reasons (*i.e.*, illiquidity effect or market frictions). We believe this is less plausible in our case. First, even the lowest beta decile portfolio still has an average daily turnover of 0.96%, making the market friction less of a concern for investors. Second, in unreported analysis, we find that the Amihud (2002) illiquidity ratio and the Hou and Moskowitz (2005) price delay measure, two conventional measures for illiquidity and frictions, could only explain 9% and 10% of the slope coefficient in beta, respectively. Therefore, the success

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volatility. Both the idiosyncratic risk and MAX5 (a range-based volatility measure) are volatility measures for stocks as well. Therefore, there is a highly positive correlation among beta, idiosyncratic volatility, and MAX5 in the cross section.

[25] It should be noted that the fraction explained by the candidate variable is not bounded from 0 to 100%. Hou and Loh (2016) noted that the decomposition procedure only requires that explained and unexplained fraction add up to 100% in total.

of turnover ratio in capturing the beta pricing pattern lends more supports to our overconfidence-based mechanism in resolving the low-beta anomaly.

[**Insert Table 7 here**]

To sum up, by linking together the portfolio evidence in **Table 6** and the "horse race" of the firm-level decomposition exercise in **Table 7**, we are able to pin down several promising variables in explaining the pervasive low-beta anomaly in the Chinese stock market. The turnover ratio, the MAX5 measure, and the IVOL measure all seem to be able to capture the pricing power of beta in the cross section. Therefore, the low-beta anomaly in China seems to be more in line with the behavioural mechanisms (Baker et al. 2011; Bali et al. 2017; Liu et al. 2018), but in contradiction to the rational, risk-based mechanisms.

### 7.2. Bivariate Portfolio Sorts

Although we mainly rely on the firm-level "horse race" to dissect the low-beta anomaly in China, for robustness purpose, we adopt the bivariate portfolio sorting procedure to further assess the beta-return relation by controlling the three behavioural variables (*i.e.*, IVOL, MAX5, and TURN) one at a time. For example, at the beginning of each month, all stocks are first sorted in ascending orders to form the quintile portfolios based on MAX5 (the first dimension). Within each of the MAX5-quintile portfolios, the composite stocks are then further assigned to five quintiles sorted on beta in ascending orders (the second dimension) to produce the 5x5 sequentially sorted portfolios. The returns of the MAX5-controlled beta-sorted quintile portfolios are then computed as the arithmetic average across the five different MAX5 quintiles (the first dimension) that belong to the same beta-sorted quintile (the second dimension). The zero-cost, high-minus-low beta portfolio is constructed by taking a long position of the highest beta quintile (Q5) and a short position of the lowest beta quintile (Q1) portfolio. If the low-beta anomaly is mainly a MAX5 story, then the high-minus-low beta portfolio would not produce a strong return differential after controlling for the MAX5 effect.

[**Insert Table 8 here**]

**Panel A of Table 8** reports the performance of the characteristics-controlled beta-sorted quintile portfolios and the associated high-minus-low beta portfolios. For brevity purpose, only the excess return and the FF5 alpha are reported. As we expected, after controlling IVOL or MAX5, the inverse relation between beta and return becomes less pronounced. The low-beta anomaly seems mainly due to the overperformance in low beta quintile (Q1), as the risk-adjusted returns are similar in magnitude from quintile 2 to quintile 5.

The most striking finding is when we control for the turnover ratio (TURN), there no long exists a low-beta anomaly: Both the excess return and the FF5 alpha is no longer statistically significant. More strikingly, high beta portfolios tend to have higher risk adjusted returns (*i.e.*, the highest three quintile portfolio all have positive alphas ranging from 20 bps to 27 bps per month, which are all statistically significant at the 10% level). The risk-adjusted return differential between Q5 and Q1 portfolios also becomes positive, though it is not statistically significant.

The fact that after controlling for the turnover ratio, beta flips its sign in predicting cross-sectional stock return (on a risk-adjusted basis) raises an interesting point that, by construction, beta should not be a *pure* behavioural measure. Therefore, if the beta anomaly is indeed driven by mispricing, then sorting on betas (with or without controlling for other firm characteristics) would not produce the largest mispricing-related return differentials between Q5 and Q1 portfolios. Therefore, we redo the bivariate portfolio sorts by first sorting on beta (in ascending orders) and assign all stocks into quintile portfolios. Within each beta-sorted quintile portfolios, composite stocks are then sequentially sorted into five quintile portfolios based on each of the three behavioural characteristics (*i.e.*, IVOL, MAX5, and TURN) in ascending orders. The beta-controlled characteristic-sorted quintile portfolio is then constructed as the arithmetic average across the five beta quintiles. The zero-cost, high-minus-low characteristics portfolio is constructed by taking a long position of the highest quintile (Q5) and a short position of the lowest quintile (Q1).

The results in **Panel B** of **Table 8** indicate that, after controlling for the beta effect by sorting first on stock betas, the negative relation between alphas and the behavioural features remains strong. For example, the lowest IVOL quintile portfolio (Q1) has a risk-adjusted return of 1.27 percentages per month, which is statistically significant at the 1% level. On the contrary, the highest IVOL quintile portfolio (Q5) has a monthly FF5 alpha of -0.65% and is also statistically significant at the 1% level. The high-minus-low IVOL portfolio yields a negative alpha of -1.91% per month with a *t*-statistics of -6.18. Compared to the beta-sorted quintile portfolio which controls for IVOL (see **Panel A**), the magnitude of the return differentials across portfolios become much more pronounced, indicating that IVOL is a stronger (negative) return predictor and possibly a better measure of lottery-like features (than stock beta). Similar patterns are also documented for the beta-controlled MAX5-sorted (TURN-sorted) quintile portfolios. The Q1 MAX5-sorted (TURN-sorted) quintile portfolio earns a positive alpha of 1.09% (0.99%) which are significant at the 1% level, while the Q5 MAX5-sorted (TURN-sorted) quintile portfolio delivers a negative alpha of -0.72% (-1.14%) with a $t$-statistics of -5.56 (-5.96).

Overall, when comparing **Panel A** and **Panel B**, the most salient features are: First, the zero cost, high-minus-low portfolio exhibits much larger return differential when sorted on "pure" behavioural measures than on stock beta. This suggests that much of the low-beta anomaly is indeed captured by the behavioural-based explanations. Second, turnover is more able to "explain" the low-beta anomaly than IVOL or MAX5, because once we controlled for turnover, the risk-adjusted return of the zero-cost, high-minus-low-beta portfolio diminishes (and even flips its sign).[26]

### 7.3. Addressing the Size Concern

A legitimate concern is whether the documented downward-sloping SML in China is a manifestation of the size effect, because our baseline results are implemented on all available stocks in the Chinese A-share market, which contains numerous small-cap stocks. Note retail investors in China has a strong preference for small-sized stocks (Han & Li 2017).

To address the size concern and also to test the robustness of the "downward-sloping" shape of the CAPM line in China, we redo the Fama-MacBeth cross-sectional regression at the firm level by removing the lowest size-quintile stocks. The lowest size quintile contains more than 20 percent of the number of stocks, but covers less than 8 percent of the total market capitalization in China.

**Table 9** presents the Fama-MacBeth regression outputs for the subsample in China. The slope coefficient on beta ranges from -1.63 to -0.72 over alternative model specifications. The bottom line is that there still exists a striking downward-sloping SML in the subsample after excluding the micro-cap stocks. In other words, stock beta remains a strong negative return predictor in the cross section. More importantly, the pricing information of stock beta is not subsumed by the conventional (cross-sectional) return predictors including size, value, profitability, investment, intermediate-term momentum, and short-term reversal.[27] However, both the magnitude and the significance of the beta coefficient becomes smaller as compared to the results in **Table 1**. These changes provide indirect

[26] These salient features of the bivariate-sorted portfolios are robust under alternative portfolio formation procedures (*i.e.*, independent portfolio sorts) and alternative weighting schemes (*i.e.*, equal- or value-weights), and thus are omitted for brevity purposes.

[27] In unreported analysis, we also rely on the cutoff point of small stocks in Liu *et al.* (2019) by excluding the bottom 30% smallest firms in the Fama-MacBeth regression. Again, we find a robust downward-sloping SML in China after accounting for the conventional return determinants including size, value, profitability, investment, intermediate-term momentum, and short-term reversal in the cross section.

evidence that the low-beta anomaly is somehow related to the size effect. This, however, is as expected, because the low-beta anomaly should be more pronounced among small-cap firms than large-cap ones for any behavioral story to make sense. It would hardly to imagine that the low-beta anomaly to appear more strongly among large-cap stocks, which tends to be monitored more closely by professional market participants (*i.e.*, fund managers).

[**Insert Table 9 here**]

### 7.4. Extensions and Robustness

In this subsection, we provide a summary of extensions and robustness checks, and their main outcomes.

**Alternative beta measures**. We are aware that the Frazzini and Pedersen (2014) beta measure is under debate (Novy-Marx & Velikov 2018). However, our key result of a downward-sloping SML in China is not driven by the specific beta measure we employ. Other popular beta measures, such as the Welch (2019) slope-winsorized beta measure and the Liu et al. (2018) beta measure, all yield very similar results. See **Appendix A.3** in the appendix for the shape of SML in China with alternative beta construction methods.

**Alternative factor models**. Our portfolio result that the low-beta stocks outperform high-beta stocks on a risk-adjusted basis is robust to alternative factor models, such as the recently proposed CH3 factor model in Liu et al. (2019). We do not rely on the Liu et al. (2019) three factors in our main analysis, because their factors are restricted from 2000 onwards, which would limit the sample period of our dataset. In fact, using their factors with the shortened sample period, the zero-cost long-and-short portfolio (*i.e.*, D10-D1) still generates a risk-adjusted return of -0.97% per month, which is significant at the 5% level.

**Transaction cost analysis**. Our key finding that the low-beta stocks outperform high-beta stocks (on a risk-adjusted basis) is robust when taking transaction cost into account. A back-of-the-envelope calculation suggests the annualized portfolio turnover for the zero-cost low-minus-high beta strategy (D1−D10 in **Section 6.4**) is around 203% per year. The breakeven transaction cost that will wipe out the FF5 alpha amounts to approximately 802 bps per month, a sufficient figure for real-world implementation.

**Orthogonalized beta component**. We are aware that other behavioural channels such as lottery demand could also (jointly) impact the pricing of beta. To demonstrate the "added value" of overconfidence in explaining the low-beta anomaly, we test the price of the beta component that is orthogonal to IVOL and MAX5. To get the orthogonal component beta, we perform the cross-sectional regression by regressing market beta on IVOL and MAX5 for each period and use the unexplained part as the orthogonalized beta. We then perform the Fama-MacBeth regression by regressing excess returns on the orthogonalized beta, while controlling for other conventional return determinants as in **Table 1**. As expected, the loading on the orthogonalized beta remain negative and significant, indicating that IVOL and/or MAX5 cannot fully capture the low-beta anomaly in China. The negative price of the orthogonalized beta, however, disappears when we add turnover into the model specification. This is consistent with our findings in the Horse Race and the bivariate portfolio sorts. That is, after control for other effects such as IVOL and MAX5, overconfidence can still have a significant effect on the low-beta anomaly in China.

## 8. Mutual Fund Evidence

This subsection looks at a particular type of real-world investors, the Chinese mutual funds, as we explore the portfolio implications with an "inverted" CAPM line in China. Frazzini and Pedersen (2014) provide US evidence that mutual fund managers tend to tilt their portfolio towards high-beta stocks, which leads to an average portfolio beta greater than one. They argue that overweighting high-beta stocks can also help these open-end funds avoid lagging behind their benchmark in a bull market because of the cash holding requirements (*i.e.*, the need to hold cash to meet redemptions). Baker et al. (2011) attribute the high beta strategy adopted by the US fund managers to the mandate of tracking the fixed benchmark, which discourage them from arbitraging away the beta anomaly.

Unlike the "flattened" CAPM line in the US, the portfolio implications (of the low-beta anomaly) could be vastly different in a market with a downward-sloping CAPM line such as in China. Actively managed, long-only mutual funds (*i.e.*, the smart money) would have a strong incentive to tilt their portfolios towards low-beta stocks rather than high-beta ones, as low-beta stocks provide higher returns on an absolute basis (and also on a risk-adjusted basis). That is, holding low-beta stocks and shying away from high-beta ones would not only increase their chances to outperform the overall market (if that is the implicit benchmark used by the fund investors), but also enhance their portfolio Sharpe ratios from a performance evaluation perspective.

In practice, fund managers in China could also adopt a hybrid strategy by combining multiple investment styles such as size, value, and low beta. Therefore, we adopt the Fama-MacBeth two-pass regression framework to examine the mutual fund performance in the cross section. In the first stage, the monthly return of an individual fund is regressed on the Fama-French five factors plus the BAB factor to obtain the factor exposures. To account for the factor that mutual funds cannot use margin by mandate, we use the unlevered rank-based BAB and equally-weighted BAB portfolios as the alternative proxy for the BAB factor. The time-series regression helps identify a fund's investment styles as it attributes the performance to different factor exposures. For example, a higher factor loading on the BAB factor (relative to the peers) suggests the fund manager tilt more towards the low-beta stocks and shy away from high-beta ones. In the second stage, a cross-sectional regression is performed, in which the individual fund returns are regressed on the factor loadings (to the Fama-French five factors and the BAB factor) obtained in the first stage.

**Table 10** provides the fund-level evidence whether professional investors actively engaging in exploiting the low-beta anomaly in China. In model specification 1, it seems that the higher the loading on the portfolio beta of these active funds, the lower the performance of the funds, which is consistent with the predictions in an "inverted" CAPM world. However, the coefficient on portfolio beta flips signs from one model specification to another, and $t$-statistics are not always significant. The loadings on the size and value factors are all statistically positive, and they explain much of the return differentials of the fund performances in the cross section ($adj. R^2$ equals 39.1% in model specification 2). Adding the factor loadings on the RMW and CMA factors also increase the ability to explain the performance of mutual funds in the cross section as $adj. R^2$ increased to 43.0% in model specification 3. In model specification 4, the factor loadings on the BAB factor is included together with the loadings on the Fama-French five factors. Note a *positive* loading on the exposure of the BAB factor indicates a fund adopts a *lower* beta strategy would earn *higher* portfolio returns (in the case of the Fama-MacBeth two-pass regression). As it stands the loading on the BAB factor is an important return determinant of the mutual fund performance, as it has a coefficient of 1.11 which is statistically significant at the 10% level. Moreover, adding the factor loading on the BAB factor increases $adj. R^2$ to 48.7%.

The most parsimonious model is the last column (model specification 5), which only includes the loadings on size, value, profitability, investment, and the BAB factor. It explains the most of the cross-sectional variations of the mutual funds ($adj. R^2 = 50.8\%$). The coefficients on the loadings to the size, value, and BAB factors are statistically and economically significant, indicating that goodperforming funds tend to tilt their portfolio holdings to small-caps, value firms, low-beta stocks, or a combination of these three. This is consistent with the firm-level evidence in **Section 4** that both size ($lnME$) and beta are negatively priced while value ($lnBTM$) is positively priced in the cross section. Therefore, these institutional investors in China have strong incentives to tilt their portfolios towards low-beta stocks rather than high-beta ones. That is, holding low-beta stocks would not only increase their chances to outperform the overall market (if that is the implicit benchmark used by the fund investors), but also enhance their portfolio Sharpe ratios from a performance evaluation perspective.

[**Insert Table 10 here**]

Overall, the results from the actively-managed open-end funds help re-establish the view that, at least, some institutional investors actively exploit the portfolio implications of an "inverted" CAPM line in China by shying away from lottery-like stocks and betting on low-beta stocks for superior performance. Such a low beta strategy increases the gross return of the fund and also enhance their portfolio Sharpe ratios from a performance evaluation perspective.

## 9. Conclusion

Arguably, the most striking finding of the article is the documented "inverted" CAPM line in China versus the typical "flattened" CAPM line in the US. The downward-sloping SML in China cannot be easily explained by existing theories of the low-beta anomaly that generally resorts to certain type of market constraints (i.e., margin or leverage constraints).

We show that investor overconfidence offers some promises in reconciling the downward-sloping SML in China. In the time-series dimension, we provide compelling evidence that the slope of the SML becomes more "inverted" subsequent to increased overconfidence after accounting for other possible economic mechanism. Moreover, we also document a *dynamic* overconfidence effect as investor overconfidence is amplified by self-attribution bias: The SML gets more inverted when investors become more overconfident due to biased self-attribution (i.e., proxied by prior market performance). In the cross section, we find that the low-beta anomaly in China is fully captured by stock turnover ratio: High-beta stocks are the most heavily traded stocks with the lowest risk-adjust returns. Both at the firm-level and the portfolio level, there is no longer a low-beta anomaly after controlling for the volume effect (i.e., turnover ratio).

A downward-sloping SML also has its distinctive portfolio implications for the mutual fund industry. In fact, the evidence from the actively managed equity funds in China reinforces the view that in a retail-investor-dominated market, some institutional investors (*i.e.*, mutual funds) actively exploit the portfolio implications of the low-beta anomaly by shying away from lottery-like stocks and betting on low-beta stocks for superior performance.

**Table 1. Fama-MacBeth Regression at the Firm Level in China**

This table reports the results of the Fama-MacBeth cross-sectional regressions at the firm level. Beta is measured as the product of correlation and the ratio of asset volatility over market volatility, using the past five-year daily returns: correlations and volatilities are separately estimated over the five (minimum three) and three (minimum one) year rolling windows, respectively. lnME is the natural logarithm of firm's market capitalization measured at the end of June in year $t$. lnBTM is the natural logarithm of firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. $\mathrm{RET}^{\mathrm{MOM}}$ is the intermediate-term return momentum, defined as the past 12-month cumulative return, skipping the most recent month. $\mathrm{RET}^{\mathrm{STREV}}$ is the short-term return reversal, defined as the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5% level. Coefficients, the time-series averages of the period-by-period cross-sectional regressions, are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey–West adjusted *t*-statistics (in brackets) with a lag length of 12 are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2016.

| | **Const.** | **Beta** | **lnME** | **lnBTM** | **OP** | **INV** | $\mathbf{RET}^{\mathbf{MOM}}$ | $\mathbf{RET}^{\mathbf{STREV}}$ | $\boldsymbol{Adj.R^2}$ | **Firms** | **Periods** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Coef. | 4.48 | -2.68 | | | | | | | 0.0186 | 1,180.77 | 246 |
| | (4.40) | (-2.70) | | | | | | | | | |
| | [3.13] | [-2.92] | | | | | | | | | |
| Coef. | 10.03 | -2.05 | -0.69 | 0.45 | | | | | 0.0608 | 1,134.97 | 246 |
| | (6.38) | (-2.30) | (-4.86) | (2.43) | | | | | | | |
| | [4.97] | [-3.90] | [-3.87] | [2.52] | | | | | | | |
| Coef. | 10.34 | -2.03 | -0.73 | 0.57 | 0.45 | 0.15 | | | 0.0668 | 1,042.71 | 246 |
| | (6.63) | (-2.21) | (-5.31) | (2.92) | (1.20) | (0.91) | | | | | |
| | [5.04] | [-3.74] | [-4.11] | [2.56] | [2.22] | [0.66] | | | | | |
| Coef. | 10.71 | -2.24 | -0.77 | 0.51 | 0.32 | 0.08 | 0.00 | -0.05 | 0.0958 | 1,042.71 | 246 |
| | (6.79) | (-2.50) | (-5.71) | (2.74) | (0.88) | (0.47) | (-0.12) | (-6.09) | | | |
| | [4.97] | [-4.47] | [-4.24] | [2.31] | [1.88] | [0.39] | [-0.08] | [-6.89] | | | |

**Table 2. Time-Variation of the Security Market Line in China, July 1996 to December 2016**

The table reports the second-stage time series regression of the intercept and slope of the SML on the (possible) economic determinants. TURN(-1) is the lagged value-weighted turnover ratio across all firms in the prior month. Sigma(-1) is the lagged return volatility, defined as the standard deviation of the market returns in prior month, EPU(-1) the lagged economic uncertainty index, ILLIQ(-1) the lagged market illiquidity measured by the value-weighted implied spread, DISP(-1) the lagged value-weighted cross-sectional return standard deviation. RMRF, SMB, HML, RMW, CMA, MOM, and STREV are the contemporaneous market, size, value, profitability, investment, momentum, and short-term reversal factors, respectively. Newey–West adjusted *t*-statistics with a lag length of 12 are reported in brackets. $Adj.R^2$ is the adjusted R-square, and Obs. is the number of observations. The sample period is between July 1996 and December 2016.

| | **Dependent Var. = Zero-beta Asset (Intercept of SML)** | | | | | | **Dependent Var. = Unit-beta Asset (Slope of SML)** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **1** | **2** | **3** | **4** | **5** | **6** |
| Const. | 3.10 | 2.93 | 3.09 | 3.06 | 3.15 | 2.91 | -2.78 | -2.63 | -2.76 | -2.73 | -2.82 | -2.59 |
| | [4.06] | [3.63] | [4.10] | [3.93] | [4.16] | [3.92] | [-3.99] | [-3.55] | [-4.03] | [-3.81] | [-4.07] | [-3.78] |
| TURN(-1) | 2.61 | 3.03 | 2.72 | 2.60 | 1.83 | 2.05 | -2.27 | -2.65 | -2.38 | -2.26 | -1.66 | -1.84 |
| | [3.01] | [3.81] | [3.22] | [3.05] | [1.65] | [1.95] | [-2.90] | [-3.66] | [-3.09] | [-2.96] | [-1.64] | [-1.95] |
| Sigma(-1) | | -1.37 | | | | -1.51 | | 1.24 | | | | 1.28 |
| | | [-1.52] | | | | [-1.77] | | [1.43] | | | | [1.57] |
| EPU(-1) | | | -0.83 | | | -0.60 | | | 0.83 | | | 0.70 |
| | | | [-0.95] | | | [-0.77] | | | [1.04] | | | [0.99] |
| ILLIQ(-1) | | | | -0.39 | | -0.55 | | | | 0.54 | | 0.71 |
| | | | | [-0.80] | | [-0.94] | | | | [1.19] | | [1.38] |
| DISP(-1) | | | | | 1.15 | 1.62 | | | | | -0.90 | -1.34 |
| | | | | | [0.77] | [0.93] | | | | | [-0.67] | [-0.87] |
| RMRF | 0.63 | 0.63 | 0.62 | 0.64 | 0.62 | 0.63 | 0.38 | 0.38 | 0.39 | 0.37 | 0.39 | 0.38 |
| | [6.36] | [6.26] | [6.55] | [6.38] | [6.86] | [6.56] | [4.12] | [4.05] | [4.33] | [3.90] | [4.55] | [4.17] |
| SMB | 0.26 | 0.34 | 0.27 | 0.27 | 0.26 | 0.36 | 0.27 | 0.20 | 0.26 | 0.26 | 0.27 | 0.18 |
| | [0.84] | [1.05] | [0.83] | [0.86] | [0.82] | [1.02] | [1.14] | [0.81] | [1.05] | [1.08] | [1.13] | [0.66] |
| HML | -1.00 | -0.96 | -1.00 | -0.99 | -1.01 | -0.96 | 0.88 | 0.85 | 0.88 | 0.87 | 0.89 | 0.84 |
| | [-2.91] | [-3.02] | [-2.84] | [-2.97] | [-2.90] | [-2.91] | [3.09] | [3.20] | [3.01] | [3.17] | [3.09] | [3.12] |
| RMW | 1.56 | 1.64 | 1.59 | 1.57 | 1.53 | 1.66 | -1.66 | -1.74 | -1.70 | -1.68 | -1.64 | -1.76 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | [3.15] | [3.17] | [3.12] | [3.12] | [3.13] | [3.06] | [-3.90] | [-3.87] | [-3.84] | [-3.84] | [-3.87] | [-3.72] |
| CMA | 1.08 | 1.08 | 1.12 | 1.07 | 1.03 | 1.04 | -1.08 | -1.09 | -1.13 | -1.07 | -1.04 | -1.06 |
| | [1.65] | [1.63] | [1.65] | [1.64] | [1.61] | [1.56] | [-1.75] | [-1.74] | [-1.76] | [-1.74] | [-1.72] | [-1.67] |
| MOM | -0.90 | -0.93 | -0.91 | -0.91 | -0.90 | -0.93 | 0.76 | 0.78 | 0.77 | 0.76 | 0.75 | 0.79 |
| | [-2.37] | [-2.52] | [-2.40] | [-2.39] | [-2.32] | [-2.52] | [2.35] | [2.52] | [2.39] | [2.38] | [2.31] | [2.54] |
| STREV | -0.62 | -0.57 | -0.62 | -0.61 | -0.65 | -0.58 | 0.59 | 0.55 | 0.59 | 0.57 | 0.61 | 0.54 |
| | [-2.60] | [-2.20] | [-2.57] | [-2.48] | [-2.65] | [-2.28] | [2.88] | [2.43] | [2.84] | [2.70] | [2.89] | [2.45] |
| $Adj.R^2$ | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 |
| Obs. | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 | 245 |

**Table 3. Betting Against Beta Strategy in China**

At the beginning of each month, all stocks ranked by their estimated *ex ante* beta and assigned to two portfolios: low and high beta portfolios. Stocks are weighted by their rankings in beta: lower (higher) beta stocks have higher weights in the low (high) beta portfolio. Low (high) beta portfolio is leveraged (deleveraged) to have a unit beta at the portfolio formation. The table then reports the time-series mean, standard deviation, the annualized Sharpe ratio, and the *ex ante* beta of the betting against beta portfolio (BAB), the long leg of the BAB strategy ($R^{Low}$), and the short-leg of the BAB strategy ($R^{High}$), respectively. Alpha is the intercept term in the regression of the Fama-French five-factor model (FF5). RMRF, SMB, HML, RMW, and CMA are the market, size, value, profitability, and investment factors, respectively. Newey–West adjusted *t*-statistics with a lag length of 12 are reported in brackets. $Adj. R^2$ is the adjusted R-square, and Obs. is the number of observations. The sample period is between July 1996 and December 2016 for China.

| | **Mean** | **Std.** | **Sharpe** | **Beta** | **Alpha** | **RMRF** | **SMB** | **HML** | **RMW** | **CMA** | $\boldsymbol{Adj. R^2}$ | **Obs.** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | *Betting Against Beta in China, July 1996 to December 2016* | | | | | | | |
| $BAB$ | 0.99 | 3.46 | 0.99 | - | 0.80 | 0.14 | 0.06 | -0.12 | 0.21 | 0.00 | 0.18 | 246 |
| | | | | | [3.16] | [4.29] | [0.86] | [-1.77] | [1.49] | [0.01] | | |
| $R^{Low}$ | 1.96 | 9.36 | 0.72 | 0.92 | 0.68 | 0.96 | 0.53 | -0.15 | -0.09 | 0.11 | 0.93 | 246 |
| | | | | | [3.23] | [39.07] | [7.16] | [-2.43] | [-0.65] | [0.85] | | |
| $R^{High}$ | 1.32 | 10.97 | 0.42 | 1.21 | -0.07 | 1.09 | 0.62 | -0.09 | -0.45 | 0.09 | 0.97 | 246 |
| | | | | | [-0.52] | [54.84] | [12.00] | [-2.40] | [-7.21] | [1.12] | | |

**Table 4. Time-series Spanning Test**

The table reports the time-series spanning tests on the Fama-French five-factors using the returns of the betting against beta ($BAB$) factor. The dependent variables, RMRF, SMB, HML, RMW, and CMA are the market, size, value, profitability, and investment factors, respectively. Panel A and B use the unlevered rank-weighed BAB factor and unlevered equally-weighted BAB factor as the explanatory variable, respectively. Newey–West adjusted $t$-statistics with a lag length of 12 are reported in brackets. The sample period is between July 1996 and December 2016.

| | **RMRF** | **SMB** | **HML** | **RMW** | **CMA** |
|---|---|---|---|---|---|
| | ***Panel A: The Unlevered, Rank-weighted BAB portfolio*** | | | | |
| Intercept | 1.38 | 1.42 | 0.76 | 0.03 | 0.13 |
| | [2.02] | [4.67] | [2.35] | [0.21] | [0.90] |
| BAB | -0.85 | -0.44 | -0.31 | 0.52 | -0.33 |
| | [-5.80] | [-4.94] | [-1.41] | [4.81] | [-2.80] |
| $Adj. R^2$ | 0.1396 | 0.1206 | 0.0551 | 0.2520 | 0.1616 |
| Obs. | 246 | 246 | 246 | 246 | 246 |

| | **RMRF** | **SMB** | **HML** | **RMW** | **CMA** |
|---|---|---|---|---|---|
| | ***Panel B: The Unlevered, Equally-weighted BAB portfolio*** | | | | |
| Intercept | 1.29 | 1.38 | 0.73 | 0.09 | 0.09 |
| | [1.90] | [4.67] | [2.36] | [0.62] | [0.64] |
| BAB | -1.28 | -0.67 | -0.44 | 0.76 | -0.47 |
| | [-6.49] | [-5.91] | [-1.39] | [5.31] | [-3.04] |
| $Adj. R^2$ | 0.1639 | 0.1443 | 0.0576 | 0.2743 | 0.1721 |
| Obs. | 246 | 246 | 246 | 246 | 246 |

**Table 5. Stock Features of the Beta-sorted Decile Portfolios**

At the end of each month, stocks are assigned to equally-weighted decile portfolios based on market beta (Beta) in ascending order. The first row reports the average value of the betas within the decile portfolio, and the second row the time-series average of the excess returns of the decile portfolios. The table then reports the average firm characteristics for firms within each decile portfolio. The firm characteristics are the log of market capitalization (lnME), the log of book-to-market equity (lnBTM), the operational profitability (OP), the investment (INV), the intermediate-term return momentum ($\mathrm{RET}^{\mathrm{MOM}}$), the short-term return reversal ($\mathrm{RET}^{\mathrm{STREV}}$), systematic skewness (SSKEW), idiosyncratic skewness (ISKEW), idiosyncratic volatility (IVOL), the average of the largest five daily returns over the prior month (MAX5), the closing price at the end of prior month (PRC), and the average turnover ratio over the prior 12 month (TURN). The last row reports the average number of stocks within the portfolio (Firms). All statistics are averaged across periods. The sample period is between July 1996 and December 2016.

| | ***Beta-sorted Decile Portfolios*** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **1 = Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10 = High** |
| Beta | 0.82 | 0.94 | 0.99 | 1.03 | 1.07 | 1.10 | 1.13 | 1.16 | 1.21 | 1.29 |
| Exret | 2.30 | 1.84 | 1.63 | 1.81 | 1.68 | 1.88 | 1.63 | 1.42 | 1.50 | 1.00 |
| lnME | 8.29 | 8.20 | 8.10 | 8.00 | 7.97 | 7.94 | 7.91 | 7.92 | 7.92 | 8.00 |
| lnBTM | -1.76 | -1.50 | -1.39 | -1.33 | -1.29 | -1.26 | -1.24 | -1.25 | -1.26 | -1.34 |
| OP | 0.25 | 0.22 | 0.20 | 0.16 | 0.16 | 0.13 | 0.12 | 0.09 | 0.07 | 0.02 |
| INV | 0.28 | 0.22 | 0.21 | 0.19 | 0.18 | 0.17 | 0.16 | 0.16 | 0.15 | 0.13 |
| $\mathrm{RET}^{\mathrm{MOM}}$ | 11.68 | 9.33 | 9.53 | 8.98 | 9.80 | 10.74 | 11.96 | 13.92 | 16.63 | 22.34 |
| $\mathrm{RET}^{\mathrm{STREV}}$ | 1.53 | 1.77 | 1.66 | 1.80 | 1.91 | 1.94 | 2.03 | 2.12 | 2.14 | 2.02 |
| SSKEW | -1.26 | -1.92 | -2.28 | -2.65 | -2.95 | -3.14 | -3.19 | -3.33 | -3.91 | -3.16 |
| ISSKEW | 0.50 | 0.55 | 0.60 | 0.61 | 0.62 | 0.62 | 0.63 | 0.62 | 0.62 | 0.60 |
| IVOL | 0.26 | 0.26 | 0.27 | 0.27 | 0.28 | 0.29 | 0.29 | 0.30 | 0.31 | 0.33 |
| MAX5 | 2.99 | 3.28 | 3.44 | 3.60 | 3.71 | 3.82 | 3.96 | 4.09 | 4.28 | 4.58 |
| PRC | 13.63 | 12.23 | 11.63 | 10.75 | 10.42 | 10.27 | 10.13 | 10.29 | 10.55 | 11.43 |
| TURN | 0.96 | 1.01 | 1.10 | 1.20 | 1.25 | 1.32 | 1.40 | 1.48 | 1.59 | 1.79 |
| Firms | 118.10 | 118.06 | 118.14 | 118.01 | 118.33 | 117.82 | 118.11 | 118.03 | 118.17 | 117.99 |

**Table 6. Univariate Portfolios Sorted on Beta**

At the end of each month, stocks are assigned to the equally-weighted decile portfolios based on their market beta (Beta) in ascending order. Exret denotes the time-series average of the excess return of the decile portfolio (in percentages). Sharpe is the annualized Sharpe ratio of the decile portfolio. Alpha is the intercept term in the regression of the CAPM model, the Fama-French three factor model (FF3), the Fama-French five factor model (FF5), the Fama-French five factor model augmented with the momentum and short-term reversal factors (FF7). Adj. Ret denotes the DGTW-adjusted returns of the decile portfolio. Newey–West adjusted *t*-statistics with a lag length of 12 are reported in brackets below the coefficients. The sample period is between July 1996 and December 2016.

| | ***Beta-sorted Decile Portfolios*** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1 = Low** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10 = High** | **10-1** |
| Exret | 2.30 | 1.84 | 1.63 | 1.81 | 1.68 | 1.88 | 1.63 | 1.42 | 1.50 | 1.00 | -1.29 |
| Sharpe | 0.90 | 0.78 | 0.70 | 0.72 | 0.67 | 0.72 | 0.60 | 0.54 | 0.55 | 0.38 | -0.73 |
| **CAPM** | | | | | | | | | | | |
| Alpha | 1.45 | 0.99 | 0.77 | 0.91 | 0.78 | 0.95 | 0.65 | 0.46 | 0.49 | -0.03 | -1.48 |
| | [3.49] | [4.77] | [3.96] | [3.98] | [3.22] | [3.73] | [2.55] | [1.86] | [1.76] | [-0.11] | [-3.73] |
| **FF3** | | | | | | | | | | | |
| Alpha | 1.00 | 0.37 | 0.12 | 0.11 | -0.09 | 0.00 | -0.37 | -0.42 | -0.57 | -0.97 | -1.97 |
| | [3.00] | [2.30] | [0.93] | [0.87] | [-0.75] | [0.02] | [-3.80] | [-3.96] | [-3.61] | [-6.01] | [-5.03] |
| **FF5** | | | | | | | | | | | |
| Alpha | 1.20 | 0.43 | 0.36 | 0.36 | 0.21 | 0.33 | -0.01 | 0.11 | -0.05 | -0.18 | -1.38 |
| | [3.19] | [2.49] | [2.11] | [2.36] | [1.54] | [2.77] | [-0.09] | [0.93] | [-0.29] | [-0.91] | [-3.14] |
| **FF7** | | | | | | | | | | | |
| Alpha | 1.12 | 0.47 | 0.34 | 0.31 | 0.15 | 0.28 | -0.01 | 0.07 | -0.12 | -0.32 | -1.44 |
| | [3.18] | [2.61] | [1.76] | [2.00] | [1.12] | [2.45] | [-0.05] | [0.51] | [-0.72] | [-1.68] | [-3.74] |
| **DGTW** | | | | | | | | | | | |
| Adj. Ret | 0.26 | 0.24 | 0.08 | 0.09 | 0.00 | 0.21 | -0.07 | -0.13 | -0.20 | -0.44 | -0.70 |
| | [1.99] | [3.13] | [1.02] | [1.33] | [0.01] | [2.42] | [-0.88] | [-1.82] | [-1.85] | [-4.49] | [-4.56] |

**Table 7. Decomposing the Low-beta Anomaly: Horse Race**

**Panel A** reports the firm-level Fama-MacBeth cross-sectional regressions. The DGTW characteristics-adjusted returns are regressed on the firm betas period by period, and the time-series average of the slope coefficients are reported in the first row, together with the Fama-MacBeth *t*-statistics (in parentheses) and the Newey-West *t*-statistics (in brackets). **Panel B** reports the final-stage of the firm-level Hou and Loh (2016) decomposition (see **Section 7.1** and **Appendix A.2**). **Explained** is the component of the slope coefficient explained by the candidate variable. **Unexplained** is the remaining component of the slope coefficient unrelated to the candidate variable. **Total** is the sum of the explained and unexplained components. The relative proportion of the explained and unexplained parts is also reported, together with their *t*-statistics in brackets. All candidate variables are defined in **Appendix A.1** and they are winsorized at the 0.5 and 99.5% level. The sample period is between July 1996 and December 2016. ***, **, and * denotes the statistical significance at the 1%, 5%, and 10% level, respectively.

The final-stage decomposition could be concisely expressed as follows:

The slope coefficient decomposed into two parts: $$\underbrace{\bar{\hat{\lambda}}_t}_{Total} = \underbrace{\overline{\hat{\lambda}(Z)_t^{Explained}}}_{Explained\ Coefficient} + \underbrace{\overline{\hat{\lambda}_t^{Unexplained}}}_{Unexplained\ Coefficient},$$

The relative proportions of the two components: $$\underbrace{100\%}_{Total} = \underbrace{\frac{\overline{\hat{\lambda}(Z)_t^{Explained}}}{\bar{\hat{\lambda}}_t}}_{Explained\ Proportion} + \underbrace{\frac{\overline{\hat{\lambda}_t^{Unexplained}}}{\bar{\hat{\lambda}}_t}}_{Unexplained\ Proportion}.$$

| | OP | INV | $RET^{STREV}$ | MAX5 | SSKEW | ISKEW | IVOL | PRC | TURN |
|---|---|---|---|---|---|---|---|---|---|
| | **Panel A: Fama-MacBeth Cross-sectional Regression (Stage 1)** | | | | | | | | |
| **Const.** | 1.60 | 1.52 | 1.55 | 1.55 | 1.55 | 1.55 | 1.50 | 1.55 | 1.14 |
| *FM t-stat.* | (2.57) | (2.44) | (2.49) | (2.49) | (2.49) | (2.49) | (2.40) | (2.49) | (1.98) |
| *NW t-stat.* | [4.42] | [3.93] | [4.06] | [4.06] | [4.06] | [4.06] | [3.96] | [4.06] | [3.23] |
| **Beta** | -1.50 | -1.43 | -1.45 | -1.45 | -1.45 | -1.45 | -1.39 | -1.45 | -1.10 |
| *FM t-stat.* | (-2.52) | (-2.38) | (-2.43) | (-2.43) | (-2.43) | (-2.43) | (-2.33) | (-2.43) | (-1.99) |
| *NW t-stat.* | [-4.43] | [-3.93] | [-4.04] | [-4.04] | [-4.04] | [-4.04] | [-3.92] | [-4.04] | [-3.35] |
| Nobs | 246 | 246 | 246 | 246 | 246 | 246 | 245 | 246 | 246 |
| $Adj.\ R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

| | OP | INV | $RET^{STREV}$ | MAX5 | SSKEW | ISKEW | IVOL | PRC | TURN |
|---|---|---|---|---|---|---|---|---|---|
| **Panel B: The Decomposition of the Slope Coefficient (Stage 3)** | | | | | | | | | |
| **Explained:** Coef. = $\overline{\hat{\lambda}(Z)_t^{Explained}}$, and Proportion = $\frac{\overline{\hat{\lambda}(Z)_t^{Explained}}}{\overline{\hat{\lambda}_t}}$ | | | | | | | | | |
| *coef.* | -0.01 | 0.05 | -0.05 | -1.43 | 0.05 | -0.06 | -1.16 | 0.12 | -1.35 |
| *Proportion* | 0 | -4 | 4 | **98** | -3 | 4 | **83** | -9 | **122** |
| *t-stat.* | [0.07] | [-0.71] | [0.44] | [2.82] | [-0.41] | [0.90] | [2.55] | [-0.85] | [2.11] |
| **Unexplained:** Coef. = $\overline{\hat{\lambda}_t^{Unexplained}}$, and Proportion = $\frac{\overline{\hat{\lambda}_t^{Unexplained}}}{\overline{\hat{\lambda}_t}}$ | | | | | | | | | |
| *coef.* | -1.50 | -1.48 | -1.39 | -0.02 | -1.50 | -1.39 | -0.23 | -1.57 | 0.25 |
| *Proportion* | 100 | 104 | 96 | 2 | 103 | 96 | 17 | 109 | -22 |
| *t-stat.* | [14.24] | [20.88] | [11.36] | [0.05] | [12.74] | [20.26] | [0.51] | [10.77] | [-0.39] |
| **Total:** Coef. = $\overline{\hat{\lambda}(Z)_t^{Explained}} + \overline{\hat{\lambda}_t^{Unexplained}} = \overline{\lambda}_t$, and Proportion = $\frac{\overline{\hat{\lambda}(Z)_t^{Explained}}}{\overline{\hat{\lambda}_t}} + \frac{\overline{\hat{\lambda}_t^{Unexplained}}}{\overline{\hat{\lambda}_t}} = 100\%$ | | | | | | | | | |
| *coef.* | -1.50 | -1.43 | -1.45 | -1.45 | -1.45 | -1.45 | -1.39 | -1.45 | -1.10 |
| *Proportion* | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Table 8. Bivariate Portfolio Sorts**

At the beginning of each month, all stocks are first sorted into quintile portfolios based on one firm characteristic (the first dimension). Within each characteristics-sorted quintile portfolio, the composite stocks are then further assigned to five subgroups based on another firm characteristic (the second dimension). The returns of second-dimension quintile portfolios are then calculated as the equally-weighted average across the first dimension to control for effect of the first characteristic. The firm characteristics are market beta (Beta), idiosyncratic volatility (IVOL), the average of the maximum five daily returns over prior month (MAX5), and average turnover ratio (TURN). Exret is the portfolio excess return and Alpha is the intercept term in the Fama-French five-factor model regression. Q5 - Q1 denotes the high-minus-low, zero cost portfolio. Newey–West adjusted $t$-statistics with a lag length of 12 are reported in brackets. The sample period is between July 1996 and December 2016.

| | **Panel A: Second Dimension = Beta** | | | | | | | **Panel B: First Dimension = Beta** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Q1 = Low** | **Q2** | **Q3** | **Q4** | **Q5 = High** | **Q5 - Q1** | | **Q1 = Low** | **Q2** | **Q3** | **Q4** | **Q5 = High** | **Q5 - Q1** |
| | IVOL-controlled Beta Portfolios | | | | | | | Beta-controlled IVOL Portfolios | | | | | |
| Exret | 1.97 | 1.64 | 1.63 | 1.58 | 1.35 | -0.62 | Exret | 2.51 | 1.99 | 1.67 | 1.31 | 0.60 | -1.91 |
| | [2.36] | [2.14] | [2.11] | [2.00] | [1.72] | [-2.55] | | [2.86] | [2.48] | [2.16] | [1.70] | [0.82] | [-6.29] |
| Alpha | 0.76 | 0.28 | 0.19 | 0.22 | 0.05 | -0.71 | Alpha | 1.27 | 0.62 | 0.26 | -0.05 | -0.65 | -1.91 |
| | [3.16] | [1.81] | [1.79] | [1.86] | [0.34] | [-2.54] | | [4.78] | [3.91] | [1.96] | [-0.39] | [-4.45] | [-6.18] |
| | MAX5-controlled Beta Portfolios | | | | | | | Beta-controlled MAX5 Portfolios | | | | | |
| Exret | 2.01 | 1.70 | 1.69 | 1.67 | 1.40 | -0.60 | Exret | 2.20 | 2.05 | 1.81 | 1.55 | 0.80 | -1.40 |
| | [2.35] | [2.17] | [2.15] | [2.09] | [1.81] | [-2.41] | | [2.61] | [2.58] | [2.29] | [1.94] | [1.03] | [-4.72] |
| Alpha | 0.66 | 0.21 | 0.20 | 0.28 | 0.22 | -0.43 | Alpha | 1.09 | 0.77 | 0.40 | -0.11 | -0.72 | -1.81 |
| | [2.75] | [1.56] | [2.05] | [2.00] | [1.68] | [-1.56] | | [4.24] | [4.20] | [2.66] | [-0.77] | [-5.56] | [-5.77] |
| | TURN-controlled Beta Portfolios | | | | | | | Beta-controlled TURN Portfolios | | | | | |
| Exret | 1.63 | 1.58 | 1.67 | 1.63 | 1.41 | -0.22 | Exret | 1.70 | 1.84 | 1.90 | 1.62 | 0.76 | -0.94 |
| | [2.07] | [2.04] | [2.13] | [2.04] | [1.83] | [-1.36] | | [2.32] | [2.40] | [2.41] | [1.94] | [0.94] | [-2.73] |
| Alpha | 0.07 | -0.01 | 0.23 | 0.20 | 0.27 | 0.20 | Alpha | 0.99 | 0.70 | 0.49 | -0.19 | -1.14 | -2.13 |
| | [0.53] | [-0.13] | [1.79] | [1.81] | [1.80] | [1.06] | | [4.68] | [3.87] | [3.57] | [-1.46] | [-5.96] | [-6.11] |

**Table 9. Fama-MacBeth Regression at the Firm Level in China, excluding Micro-cap Stocks**

This table reports the results of the Fama-MacBeth cross-sectional regressions at the firm level, excluding the micro-cap stocks (*i.e.*, the bottom quintile stocks in terms of market capitalization). Beta is measured as the product of correlation and the ratio of asset volatility over market volatility, using the past five-year daily returns: correlations and volatilities are separately estimated over the five (minimum three) and three (minimum one) year rolling windows, respectively. lnME is the natural logarithm of firm's market capitalization measured at the end of June in year $t$. lnBTM is the natural logarithm of firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. $\mathrm{RET^{MOM}}$ is the intermediate-term return momentum, defined as the past 12-month cumulative return, skipping the most recent month. $\mathrm{RET^{STREV}}$ is the short-term return reversal, defined as the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5% level. Coefficients, the time-series averages of the period-by-period cross-sectional regressions, are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey–West *t*-statistics (in brackets) with a lag length of 12 are reported below the corresponding coefficients, respectively. $Adj. R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2016.

| | Const. | Beta | lnME | lnBTM | OP | INV | $\mathrm{RET^{MOM}}$ | $\mathrm{RET^{STREV}}$ | $Adj. R^2$ | Firms | Periods |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Coef. | 2.11 | -0.72 | | | | | | | 0.0211 | 916.98 | 246 |
| | (2.46) | (-0.79) | | | | | | | | | |
| | [2.03] | [-1.10] | | | | | | | | | |
| Coef. | 7.44 | -1.53 | -0.46 | 0.47 | | | | | 0.0602 | 897.20 | 246 |
| | (4.73) | (-1.72) | (-3.23) | (2.39) | | | | | | | |
| | [4.23] | [-2.74] | [-2.92] | [2.57] | | | | | | | |
| Coef. | 7.79 | -1.37 | -0.52 | 0.60 | 0.57 | 0.08 | | | 0.0662 | 827.31 | 246 |
| | (4.98) | (-1.50) | (-3.80) | (2.88) | (1.54) | (0.49) | | | | | |
| | [4.31] | [-2.34] | [-3.39] | [2.79] | [2.68] | [0.46] | | | | | |
| Coef. | 8.01 | -1.63 | -0.55 | 0.53 | 0.40 | 0.01 | 0.00 | -0.05 | 0.0967 | 827.31 | 246 |
| | (5.08) | (-1.82) | (-4.07) | (2.69) | (1.09) | (0.06) | (0.18) | (-5.69) | | | |
| | [4.26] | [-3.07] | [-3.52] | [2.52] | [2.02] | [0.07] | [0.13] | [-6.40] | | | |

**Table 10. The Cross Section of Actively Managed Mutual Funds**

The table reports the second stage cross-sectional regression of the Fama-MacBeth two-pass methodology. In the first stage time-series regression, the returns of each open-end equity fund are regressed on the Fama-French five factors (RMRF, SMB, HML, RMW, and CMA) and the betting against beta (BAB) factor to obtain the factor loadings. In the second stage, the average excess returns of the mutual funds are regressed on the factor loadings obtained in the first stage. Panel A and B use the unlevered rank-weighed and unlevered equally-weighted BAB factors, respectively. The Newey–West adjusted *t*-statistics with a lag length of 12 are reported in brackets. The sample period is between March 2010 and December 2016.

| | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| | ***Panel A: the unlevered, rank-weighted BAB factor*** | | | | |
| Alpha | 1.42 | -0.75 | -0.50 | 0.37 | 0.05 |
| | [1.41] | [-1.22] | [-0.62] | [0.41] | [0.46] |
| $\beta^{RMRF}$ | -1.30 | 1.01 | 0.59 | -0.33 | |
| | [-1.36] | [1.64] | [0.68] | [-0.32] | |
| $\beta^{SMB}$ | | 1.08 | 0.74 | 0.58 | 0.63 |
| | | [5.06] | [2.31] | [1.85] | [3.24] |
| $\beta^{HML}$ | | 0.87 | 0.95 | 0.97 | 0.98 |
| | | [4.46] | [4.00] | [4.87] | [4.97] |
| $\beta^{RMW}$ | | | 0.54 | 0.18 | 0.19 |
| | | | [2.25] | [1.20] | [1.25] |
| $\beta^{CMA}$ | | | -0.37 | 0.10 | 0.08 |
| | | | [-1.93] | [0.38] | [0.38] |
| $\beta^{BAB}$ | | | | 1.11 | 1.05 |
| | | | | [1.87] | [2.29] |
| $Adj.R^2$ | 0.00 | 0.39 | 0.43 | 0.49 | 0.51 |
| | **1** | **2** | **3** | **4** | **5** |
| | ***Panel B: the unlevered, equally-weighted BAB factor*** | | | | |
| Alpha | 1.51 | -0.70 | -0.47 | 0.33 | 0.06 |
| | [1.45] | [-1.14] | [-0.58] | [0.35] | [0.47] |
| $\beta^{RMRF}$ | -1.40 | 0.96 | 0.57 | -0.28 | |
| | [-1.41] | [1.56] | [0.66] | [-0.27] | |
| $\beta^{SMB}$ | | 1.10 | 0.75 | 0.60 | 0.64 |
| | | [5.12] | [2.37] | [1.84] | [3.16] |
| $\beta^{HML}$ | | 0.88 | 0.95 | 0.97 | 0.98 |
| | | [4.57] | [4.01] | [4.74] | [4.86] |
| $\beta^{RMW}$ | | | 0.52 | 0.25 | 0.25 |
| | | | [2.26] | [1.52] | [1.53] |
| $\beta^{CMA}$ | | | -0.35 | 0.04 | 0.02 |
| | | | [-1.82] | [0.16] | [0.12] |
| $\beta^{BAB}$ | | | | 0.64 | 0.61 |
| | | | | [1.72] | [2.17] |
| $Adj.R^2$ | 0.00 | 0.41 | 0.44 | 0.48 | 0.50 |

## Appendix

### A.1. Variable Definition

| Notation | Definition |
|---|---|
| Beta | Market beta, defined as the return sensitivity to the market portfolio. Instead of running a CAPM regression, the market beta is constructed as the product of the return correlation (with the market portfolio) and the market-adjusted volatility, using the following analytical expression in Frazzini and Pedersen (2014). $$\hat{\beta}_i^{TS} = \hat{\rho} \times \frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$ First, to account for the fact that correlations moves much slower than (conditional) volatility, two separate rolling windows with different window length are employed: A past one-year rolling window of daily returns are used to calculate the standard deviation for the volatilities and a past five-year horizon of daily returns are used for the correlation. Second, the market-adjusted volatility is calculated using one-day log-returns, while the correlation is constructed from overlapping three-day log-returns, $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln\left(1 + r_{t+k}^{i}\right)$, to control for nonsynchronous trading (which affects only correlations). I require at least six months (120 trading days) of non-missing data to estimate volatilities and at least three years (750 trading days) of non-missing return data for correlations. To reduce the influence of outliers, a Bayesian estimator is employed, which follows Vasicek (1973) by shrinking the time series estimate of beta $\beta_i^{TS}$ toward the cross-sectional mean $\beta^{XS}$. $$\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + (1 - w_i)\hat{\beta}^{XS}$$ Following Frazzini and Pedersen (2014), I set $w_i$=0.6, and $\hat{\beta}^{XS} = 1$ for all period and all assets. |
| ME and lnME | The market capitalization and the natural logarithm of the market capitalization of a stock, defined as the (natural logarithm of) firm's total market capitalization measured at the end of June in year $t$. |
| BTM and lnBTM | The book-to-market ratio and the natural logarithm of the book-to-market ratio, defined as the (natural logarithm of) firm's book-to-market equity measured at the fiscal year ending in $t-1$. |
| OP | Operational profitability, defined as the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$, which follows from Fama and French (2017). |
| INV | Asset investments, defined as the growth rate of total assets for the fiscal year ending in $t-1$, which follows from Fama and French (2017). |

| | |
|---|---|
| $\text{RET}^{\text{MOM}}$ | Intermediate-term return momentum, defined as the cumulative returns over the past 12-month rolling window, skipping the most recent month according to Fama and French (2012). |
| SSKEW | Systematic skewness (also known as co-skewness), defined as in Harvey and Siddique (2000), is calculated as the slope coefficient on the squared market terms in the following regression. $$R_i - RF = \alpha_i + \beta_i RMRF + \gamma_i RMRF^2 + \varepsilon_i$$ The above regression is performed using daily observations over the past 12-month rolling window. The estimation procedure is repeated each month to obtain the *ex ante* SSKEW measure for each month. |
| ISKEW | Idiosyncratic skewness, defined as the skewness of the daily residual terms obtained from the same regression used to calculate the (monthly) SSKEW measure. |
| IVOL | The idiosyncratic volatility, defined similarly as in Ang et al. (2006), which is the standard deviation of the residuals from the following regression. $$R_i - RF = \alpha_i + \beta_i^{RMRF} RMRF + \beta_i^{SMB} SMB + \beta_i^{HML} HML + \varepsilon_i$$ The *ex ante* IVOL measure is constructed using the above Fama-French three-factor model using daily observations over the prior month, which requires at least ten observations to run the regression. |
| MAX5 | The lottery demand measure, defined as the average of the largest five daily returns in the prior month (Bali et al. 2011; Bali et al. 2017). |
| PRC | Price level, defined as the unadjusted closing price at the end of the prior month. |
| $\text{RET}^{\text{STREV}}$ | Short-term return reversal, defined as the one-month stock returns in the prior month (Jegadeesh & Titman 1993). |
| TURN | Turnover ratio, defined as the average daily turnover ratio over the past one-month rolling window. |

### A.2. The Hou and Loh (2016) Horse Race

The Hou and Loh (2016) decomposition exercise proceeds in three stages.

**Stage 1**: The univariate Fama-MacBeth cross-sectional regression.

For each period, the excess returns of stocks are regressed on the *ex ante* market beta.

$$Ret_{it} - RF_t = \hat{a}_t + \hat{\lambda}_t \times \beta_{i,t-1} + \epsilon_{i,t} \qquad \text{[A1]}$$

The time series of the slope coefficient, $\hat{\lambda}_t$, capturing the negative beta-return relation, is retained for the final stage.

**Stage 2**: The orthogonalization procedure on the lagged correlation.

A cross-sectional orthogonalization regression is performed for each month, which regresses the stock beta on one candidate variable $Z$ (*i.e.*, one firm characteristic). The orthogonalization procedure partitions the lagged stock beta $\beta_{i,t-1}$ into two orthogonal parts: The explained part due to the candidate variable $Z$ (denoted as $\beta(Z)_{i,t-1}^{Explained}$), and the unexplained part orthogonal to the candidate variable $Z$ (denoted as $\beta_{i,t-1}^{Unexplained}$). That is, $\beta_{i,t-1} = \beta(Z)_{i,t-1}^{Explained} + \beta_{i,t-1}^{Unexplained}$. The time series of the two orthogonal parts is also retained for the final stage.

**Stage 3**: Decomposition of the time-series average of the slope coefficient $\overline{\hat{\lambda}_t}$.

In the final stage, the time series of $\hat{\lambda}_t$ (from stage 1) is decomposed into two components based on the two orthogonal parts of $\beta_{i,t-1}$ (from stage 2) and the properties of covariance (*i.e.*, $\underbrace{\frac{Cov(Ret_{i,t}-RF_t,\beta_{i,t-1})}{Var(\beta_{i,t-1})}}_{\hat{\lambda}_t} = \underbrace{\frac{Cov(Ret_{i,t}-RF_t,\beta(Z)_{i,t-1}^{Explained})}{Var(\beta_{i,t-1})}}_{\hat{\lambda}(Z)_t^{Explained}} + \underbrace{\frac{Cov(Ret_{i,t}-RF_t,\beta_{i,t-1}^{Unexplained})}{Var(\beta_{i,t-1})}}_{\hat{\lambda}_t^{Unexplained}}$).

Thus, the time-series average of the slope coefficient $\overline{\hat{\lambda}_t}$ has an explained component due to the candidate variable $Z$, denoted as $\overline{\hat{\lambda}(Z)_t^{Explained}}$, and a remaining unexplained component, denoted as $\overline{\hat{\lambda}_t^{Unexplained}}$. The final-stage decomposition could be concisely expressed as follows:

In levels: $$\underbrace{\overline{\hat{\lambda}_t}}_{Total} = \underbrace{\overline{\hat{\lambda}(Z)_t^{Explained}}}_{Explained\ Coefficient} + \underbrace{\overline{\hat{\lambda}_t^{Unexplained}}}_{Unexplained\ Coefficient}, \qquad \text{[A2]}$$

or in relative terms: $$\underbrace{100\%}_{Total} = \underbrace{\frac{\overline{\hat{\lambda}(Z)_t^{Explained}}}{\overline{\hat{\lambda}_t}}}_{Explained\ Proportion} + \underbrace{\frac{\overline{\hat{\lambda}_t^{Unexplained}}}{\overline{\hat{\lambda}_t}}}_{Unexplained\ Proportion}. \qquad \text{[A3]}$$

### A.3. The Shape of SML in China with Alternative Beta Construction Methods

Our key finding of a downward-sloping SML in China is not driven by the specific beta measure we employ. As can be seen below, the results are robust under the alternative beta measures:

[1]. The shape of SML estimated by Welch (2019)'s market beta, which uses one-year daily return with slope-winsorization and exponential decaying weights.

$$Ret_i - RF = \underset{\substack{(4.63) \\ [3.11]}}{3.34} - \underset{\substack{(-2.74) \\ [-3.05]}}{1.69} \times \beta_i + \varepsilon_i \quad \text{[A3.1]}$$

[2]. The shape of SML estimated by Liu et al. (2018)'s market beta, which uses five years of monthly returns with a one-lag Dimson (1979) correction and Vasicek (1973) shrinkage.

$$Ret_i - RF = \underset{\substack{(4.68) \\ [2.82]}}{2.98} - \underset{\substack{(-3.00) \\ [-2.64]}}{1.33} \times \beta_i + \varepsilon_i \quad \text{[A3.2]}$$

[3]. The shape of SML estimated by the conventional rolling-window market beta, which uses five-year monthly returns.

$$Ret_i - RF = \underset{\substack{(4.19) \\ [2.97]}}{2.89} - \underset{\substack{(-3.27) \\ [-3.54]}}{1.17} \times \beta_i + \varepsilon_i \quad \text{[A3.3]}$$

[4]. The shape of SML estimated by the explanatory beta, which follows Jegadeesh et al. (2019).

$$Ret_i - RF = \underset{\substack{(4.52) \\ [2.88]}}{3.78} - \underset{\substack{(-2.62) \\ [-2.49]}}{2.06} \times \beta_i + \varepsilon_i \quad \text{[A3.4]}$$

[5]. The shape of SML estimated by the instrumental beta, which follows Jegadeesh et al. (2019).

$$Ret_i - RF = \underset{\substack{(4.02) \\ [2.67]}}{3.63} - \underset{\substack{(-2.24) \\ [-2.21]}}{1.97} \times \beta_i + \varepsilon_i \quad \text{[A3.5]}$$

[6]. The shape of SML estimated by the EIV-corrected market beta, which follows Kim and Skoulakis (2018).

$$Ret_i - RF = \underset{\substack{(4.21) \\ [3.24]}}{4.08} - \underset{\substack{(-2.59) \\ [-3.27]}}{2.37} \times \beta_i + \varepsilon_i \quad \text{[A3.6]}$$

**Table A1. Fama-MacBeth Regression at the Firm Level in the US, July 1996 to December 2016**

This table reports the results of the Fama-MacBeth cross-sectional regressions at the firm level. Beta is measured as the product of correlation and the ratio of asset volatility over market volatility, using the past five-year daily returns: correlations and volatilities are separately estimated over the five (minimum three) and three (minimum one) year rolling windows, respectively. lnME is the natural logarithm of firm's market capitalization measured at the end of June in year $t$. lnBTM is the natural logarithm of firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. $\mathrm{RET}^{\mathrm{MOM}}$ is the intermediate-term return momentum, defined as the past 12-month cumulative return, skipping the most recent month. $\mathrm{RET}^{\mathrm{STREV}}$ is the short-term return reversal, defined as the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5% level. Coefficients, the time-series averages of the period-by-period cross-sectional regressions, are reported in the first row. Fama-MacBeth *t*-statistics (in parentheses) and Newey–West adjusted *t*-statistics (in brackets) with a lag length of 12 are reported below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2016.

| | **Const.** | **Beta** | **lnME** | **lnBTM** | **OP** | **INV** | $\mathbf{RET}^{\mathbf{MOM}}$ | $\mathbf{RET}^{\mathbf{STREV}}$ | $\boldsymbol{Adj.R^2}$ | **Firms** | **Periods** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Coef. | 0.99 | 0.10 | | | | | | | 0.0245 | 3,992.47 | 246 |
| | (2.98) | (0.16) | | | | | | | | | |
| | [2.13] | [0.16] | | | | | | | | | |
| Coef. | 1.43 | 0.40 | -0.10 | 0.27 | | | | | 0.0420 | 3,832.50 | 246 |
| | (4.09) | (0.56) | (-1.32) | (3.10) | | | | | | | |
| | [3.12] | [0.54] | [-1.19] | [2.55] | | | | | | | |
| Coef. | 1.47 | 0.46 | -0.11 | 0.24 | 0.20 | -0.51 | | | 0.0453 | 3,829.54 | 246 |
| | (4.26) | (0.66) | (-1.54) | (3.00) | (2.58) | (-6.53) | | | | | |
| | [3.25] | [0.63] | [-1.43] | [2.51] | [2.13] | [-5.33] | | | | | |
| Coef. | 1.31 | 0.20 | -0.08 | 0.26 | 0.19 | -0.51 | 0.06 | -3.69 | 0.0551 | 3,828.03 | 246 |
| | (3.91) | (0.33) | (-1.25) | (3.51) | (2.67) | (-6.61) | (0.29) | (-6.44) | | | |
| | [2.82] | [0.29] | [-1.03] | [2.73] | [2.26] | [-5.65] | [0.19] | [-5.98] | | | |

**Table A2. Betting Against Beta Strategy in the US, July 1996 to December 2016**

At the beginning of each month, all stocks ranked by their estimated *ex ante* beta and assigned to two portfolios: low and high beta portfolios. Stocks are weighted by their rankings in beta: lower (higher) beta stocks have higher weights in the low (high) beta portfolio. Low (high) beta portfolio is leveraged (deleveraged) to have a unit beta at the portfolio formation. The table then reports the time-series mean, standard deviation, the annualized Sharpe ratio, and the *ex ante* beta of the betting against beta portfolio (BAB), the long leg of the BAB strategy ($R^{Low}$), and the short-leg of the BAB strategy ($R^{High}$), respectively. Alpha is the intercept term in the regression of the Fama-French five-factor model (FF5). RMRF, SMB, HML, RMW, and CMA are the market, size, value, profitability, and investment factors, respectively. Newey–West adjusted *t*-statistics with a lag length of 12 are reported in brackets. $Adj. R^2$ is the adjusted R-square, and Obs. is the number of observations. The sample period is between July 1996 and December 2016 for the US.

| | **Mean** | **Std.** | **Sharpe** | **Beta** | **Alpha** | **RMRF** | **SMB** | **HML** | **RMW** | **CMA** | $Adj. R^2$ | **Obs.** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | ***Betting Against Beta in the US, July 1996 to December 2016*** | | | | | | | |
| $BAB$ | 0.83 | 4.38 | 0.66 | - | 0.49 | -0.06 | 0.17 | 0.22 | 0.72 | 0.13 | 0.34 | 246 |
| | | | | | [1.33] | [-0.55] | [1.35] | [1.28] | [4.40] | [0.51] | | |
| $R^{Low}$ | 1.17 | 3.80 | 1.07 | 0.63 | 0.43 | 0.61 | 0.48 | 0.30 | 0.10 | 0.00 | 0.74 | 246 |
| | | | | | [2.31] | [11.87] | [8.03] | [3.95] | [1.92] | [-0.01] | | |
| $R^{High}$ | 1.14 | 9.00 | 0.44 | 1.33 | 0.19 | 1.32 | 0.82 | 0.38 | -0.64 | -0.12 | 0.87 | 246 |
| | | | | | [0.63] | [20.54] | [7.04] | [3.08] | [-4.28] | [-0.39] | | |

**Table A3. Conditional Patterns of the Security Market Line in China, July 1996 to December 2016**

The table reports the second-stage time series regression of the intercept and slope of the SML on the (possible) economic mechanisms. TURN(-1) is the lagged value-weighted turnover ratio averaged across all firms in the prior month. Market performance (MS) is a dummy variable that equals one when the cumulative market return over the prior 6 months is positive and zero otherwise. $MRET$ is the magnitude of the average market returns over the prior 6 months. The control variables (Controls) includes all other variables defined in **Table 2**. Newey–West adjusted $t$-statistics with a lag length of 12 are reported in brackets. $Adj.R^2$ is the adjusted R-square, and Obs. is the number of observations. The sample period is between July 1996 and December 2016.

| | **Dependent Var. = Zero-beta Asset (Intercept of SML)** | | | **Dependent Var. = Unit-beta Asset (Slope of SML)** | | |
|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **1** | **2** | **3** |
| Const. | 2.91 | 0.65 | 0.65 | -2.59 | -0.40 | -0.44 |
| | [3.92] | [0.89] | [0.77] | [-3.78] | [-0.63] | [-0.60] |
| MS | | 2.87 | 2.50 | | -2.85 | -2.49 |
| | | [2.22] | [1.92] | | [-2.35] | [-2.08] |
| TURN(-1)×MS | | 3.74 | | | -3.40 | |
| | | [3.85] | | | [-3.87] | |
| TURN(-1)×MRET | | | 0.56 | | | -0.49 |
| | | | [2.49] | | | [-2.41] |
| TURN(-1) | 2.05 | -0.93 | -0.27 | -1.84 | 0.92 | 0.25 |
| | [1.95] | [-0.86] | [-0.20] | [-1.95] | [0.94] | [0.21] |
| Controls | YES | YES | YES | YES | YES | YES |
| $Adj.R^2$ | 0.34 | 0.35 | 0.36 | 0.43 | 0.44 | 0.45 |
| Obs. | 245 | 245 | 245 | 245 | 245 | 245 |

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