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

Xing Han[a,1], Kai Li[b], Youwei Li[c]

[a]*Department of Accountancy and Finance, University of Otago, 60 Clyde Street, 9016 Dunedin, NZ*

[b] *University of Technology Sydney, Business School, PO Box 123, Broadway, NSW 2007, Australia*

[c] *School of Management, Queen's University Belfast, 185 Stranmillis Road, BT9 5EE Belfast, UK*

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Abstract

Unlike the typical "flattened" security market line (SML) in the US, we document a highly downward sloping SML line in China, which cannot be explained by existing theories of low-beta anomaly. We provide a novel theoretical model to address the puzzling low-beta anomaly in China. In the time-series dimension, we provide compelling evidence that the slope of the SML line becomes more "inverted" when investors become overconfident with increased trading volume. In the cross section, we find consistent evidence that high-beta stocks are the most traded stocks and are linked with the lowest risk-adjusted returns, implying a much stronger betting-against-beta phenomenon in China. Finally, mutual fund evidence in China reinforces the view that institutional investors actively exploit the portfolio implications of a downward sloping SML line by shying away from high-beta stocks and betting on low-beta stocks for superior performance.

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[1] Corresponding author: Department of Accountancy and Finance, University of Otago, 60 Clyde Street, Dunedin 9016, New Zealand. Tel.: +64-(0)3 479 9066. Fax: +64 (0)3 479 8171. E-mail: xing.han@otago.ac.nz (X. Han).
E-mail addresses: xing.han@otago.ac.nz (X. Han), kai.li@uts.edu.au (K. Li), y.li@qub.ac.uk (Y. Li).
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1. Introduction

As an important pillar in modern finance, the Sharpe (1964) and Lintner (1965) capital asset pricing model (CAPM) posits that the reward (*i.e.*, expected return) of a stock is fully consummated with its quantity of systematic risk measured by beta. For example, a stock with a beta value of two should be compensated by two times the market risk premium. Therefore, the CAPM model predicts an *upward sloping* security market line (SML) in the cross section.

Empirically, however, it is a well-established fact in the US that market beta does a poor job in explaining the dispersion of stock returns in the cross section. First, exposure to market beta is "unpriced" at the *firm* level, indicating a typical "flattened" SML line in the US (Fama & French 1992). Moreover, 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). Second and more interestingly, portfolios of low-beta (high-beta) stocks earn higher (lower) returns than implied by the CAPM, the so-called *low beta* anomaly (Friend & Blume 1970; Haugen & Heins 1975; Baker *et al.* 2011). 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; 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 "betting against beta" strategy (BAB) designed for hedge funds, which levered up low beta stocks in the long leg and deleveraged high beta stocks in the short leg.

This study reconsiders the *low beta* anomaly from the perspective of the emerging markets. We present new empirical evidence from China, the largest emerging financial markets. Unlike the typical "flattened" SML line in the US (and other developed markets), we document a highly "downward-sloping" SML line in China. Strikingly, this strong negative beta-return relation is robust after accounting for other well-known return determinants in the cross section. Apparently, the downward sloping SML line in China indicates that the *low beta* anomaly is much more pronounced in China than in the US.

Although both a "flattened" or an "inverted" SML line would induce the low-beta anomaly in the cross section, the strongly negative slope of the security market line found in China cannot be easily reconciled with the existing theories of low risk anomaly that usually attribute to a certain type of constraints (Baker *et al.* 2011; Frazzini & Pedersen 2014; Schneider *et al.* 2015; Bali *et al.* 2017; Liu *et al.* 2018). Therefore, we propose a novel theoretical model to rationalize the negative slope of the security market line observed in China. Our model explores the overconfidence mechanism in the investment decision making process, a valid behavioural mechanism which is under-explored in the setting of low risk anomaly (Baker *et al.* 2011). Investor Overconfidence is a key feature in the emerging market context for good reasons: First, the market is populated by millions of unsophisticated individual investors who might be extremely overconfident about their valuation or trading skills. Second, in general, there are strong policy uncertainties caused by the regulatory body in the emerging markets. Overconfident investors might not be able to fully understand the policy implications and thus underestimate the asset risks, another key mechanism in our theoretical model. Overall, what sets our model apart from other competing theories lies in its time-series implication: An increase in investor overconfidence, manifested by excessive trading volume, reduces the (conditional) slope of the SML line. In other words, the slope of the SML becomes more "inverted" following excessive trading volume. Under maintained conditions, it also offers a unique solution to the "inverted" SML line in China.

In the cross-sectional dimension, our model shares the same prediction with other competing theories that high- (low-) beta stocks have lower (higher) alphas. Both firm-level and portfolio-level evidence confirms that low-beta stocks are linked with high risk-adjusted returns in China.

Based on the intuition of our model and the empirical fact that investor who are overly confident about their information or skills tend to trade the most, and also lose the most (Odean 1999; Barber & Odean 2000), we test whether stock-level trading volume could explain the low-beta puzzle in China. Therefore, we perform an extensive "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 such an extensive, firm-level analysis in China seems to weigh more on our 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 as it is consistent with further evidence from bivariate portfolio sorts as well.

Finally, we explore the down-sloping SML line in China with mutual fund data. A key difference between an inverted SML line vis-à-vis a "flattened" SML line lies in its portfolio implication. With a "flattened" SML line as in the US, more constrained investors hold riskier stocks (*i.e.*, high-beta ones) as explained in Frazzini and Pedersen (2014). This could also partially due to the fixed benchmark faced by fund managers which discourages their arbitrage activities (Baker *et al.* 2011). In a market with a downward sloping SML line, 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). Therefore, we test whether professional fund managers actively engage in low beta strategy in China. 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. In other words, superior fund performance is partially contributed by the low risk strategy adopted by the managers.

The structure of the paper is as follows. Section 2 provides a summary of the relevant literature. Section 3 describes the sample data, data sources, and the empirical shapes of the SML line in China (and the US). Section 4 presents the theoretical CAPM model augmented with investor overconfidence and develops the testable hypotheses. Section 5 provides time-series evidence and tests the two time-series predictions of the theoretical model. Section 6 provides cross-sectional evidence, including the betting against beta strategy, portfolio-level firm characteristics, and the performance of the beta-sorted decile portfolios. Section 7 performs robustness checks and further analysis, including the firm-level "horse race" and bivariate portfolio sorts. Section 8 explores the portfolio implications of the negatively sloped SML line in China with mutual fund evidence. Section 9 discusses the implications of the findings and concludes.

2. Literature Review

The embarrassment that high-beta stocks consistently underperform low-beta stocks over almost a century can be considered "the greatest anomaly in finance (Baker *et al.* 2011)." More strikingly, the low beta anomaly is a pervasive phenomenon in the financial markets, which also exists in, among others, international equities, treasury bonds, corporate bonds, and futures markets (Frazzini & Pedersen 2014). Since Black (1972), the mystery of the low beta anomaly has drawn substantial interests among academics in searching for valid theoretical justification.

The low beta anomaly could be easily reconciled with the traditional risk-based asset pricing theory, if there exists some latent risk factor(s) which captures the time-series variation of the beta-sorted portfolios in a meaningful manner. For example, Schneider *et al.* (2015) provide a rational, theoretical justification for the "anomalous" returns associated with the low beta strategy. Following Kraus and Litzenberger (1976) and Harvey and Siddique (2000), they incorporate higher moments of the market returns as additional systematic factor into the CAPM framework. That is, the pricing kernel is a (linear) function of the market return and the squared market return. With the two-factor pricing kernel, they show that the CAPM beta, which ignores the coskewness effect on asset price, systematically overestimates the risk of high-beta stocks. Empirically, they demonstrate that high beta stocks perform relatively well in bad times, and thus should command lower returns than perceived by their CAPM beta. Similar notion has been expressed, for example, in Li *et al.* (2016) who argue that high risk stocks could offer consumption-hedging benefits by performing better during weak economic conditions. That is, the low beta anomaly (and more broadly the low volatility anomaly) could be driven by a latent systematic risk as suggested by Ang *et al.* (2009). However, results from the Daniel and Titman (1997) asset-pricing tests do not seem to lend much support for the covariance explanation (*i.e.*, latent systematic factor) according to Li *et al.* (2016).

Frazzini and Pedersen (2014) provide an alternative, quasi-rational explanation for the low beta anomaly. Following the margin CAPM framework developed in Black (1972), in which mean-variance optimizers (*i.e.*, heterogeneous investors) differ in their ability to use leverage, Frazzini and Pedersen (2014) posit that *more* leverage-constrained investors (*i.e.*, mutual funds) tend to adopt a higher risk strategy by overweighting high beta stocks to lift up their portfolio beta. Their aversion to use leverage drives up the demand for high beta stocks, leading to a lower reward for these stocks on a risk-adjusted basis (Asness *et al.* 2012). Exploiting the leverage aversion, a betting against beta strategy yields a five-factor alpha of 0.55 percentages per month between 1926 and 2012 in the US stock market (See table 3 in Frazzini & Pedersen 2014). Using fund holding data, Frazzini and Pedersen (2014) document that mutual funds tend to hold above-average beta stocks, consistent with the prediction of the margin CAPM that more constrained investors hold riskier stocks.

Despite the appeal of the above rational and quasi-rational explanations, recent work, however, offers new perspectives. A prevailing view from the behavioural literature posits that the tendency to hold high beta (or high volatility) stocks are irrational. Bali *et al.* (2017) link the high-alpha, low-beta anomaly to the excessive demand (by gamblers) for lottery-like stocks. Their intuition follows directly from Kumar (2009) that lottery investors exert a strong price pressure for stocks with *perceived* high probabilities of large short-term up moves in the stock price. Such up moves are partially captured by the return sensitivities to the overall market (*i.e.*, beta). Under the framework of the cumulative prospect theory, Barberis and Huang (2008) attribute the lottery demand to investors willingness to *overpay* for the small probability of a dramatic up moves exhibited by positive skewed stocks. Empirically, Bali *et al.* (2017) demonstrate that the beta anomaly is no longer detected in these beta-sorted portfolios, after controlling for the lottery-demand features measured by MAX (*i.e.*, the average of the top five daily returns over the prior month).

Liu *et al.* (2018) provide a somewhat different view which links the low beta anomaly to the sentiment-induced mispricing. They attribute the beta anomaly to the existence of short-sales constraints and arbitrage asymmetry (Stambaugh *et al.* 2015). Accordingly, Liu *et al.* (2018) document a strongly positive (cross-sectional) correlation between CAPM beta and idiosyncratic volatility. Due to the "guilty" association with idiosyncratic volatility, high beta stocks offer low average returns (Ang *et al.* 2006, 2009) and thus, the low beta anomaly is mainly concentrated among the most overpriced stocks, but not the undervalued stocks. In other words, the low beta anomaly is more of a sub-market phenomenon due to mispricing (*i.e.*, a non-monotonic relation). Interestingly, however, Auer and Schuhmacher (2015) offer counter evidence that the betting-against-beta strategy remain profitable with Dow Jones Industrial Average stocks (*i.e.*, the largest US companies), which are probably less likely to be the most overpriced stocks.

Arguably, the above lottery demand hypothesis (i.e., the preference for gambling) and the idiosyncratic-volatility-based explanation are not the only behavioural justifications for the low beta effect. Baker *et al.* (2011) provide an interesting summary on the possible, legitimate behavioural mechanisms for the documented low beta anomaly. First, not all high beta stocks turn out to be a disappointment. Some of these high-risk stocks might even become a huge investment success. Aspired by these "legacies", naïve investors (who suffer from the *representativeness bias*) would imitate the seemingly successful strategy by betting on highly volatile stocks. Second, *overconfidence*, as another legitimate behavioural reason, might also plays an important role. Overconfident investors are more likely to engage in excessive trading volume and exert huge price pressure for volatile stocks, as they tend to overestimate their own trading skills and (falsely) believe in the precision of their price estimates (Statman *et al.* 2006). Baker *et al.* (2011) contend that the extent of self-attribution bias is likely higher for more uncertain outcomes (*i.e.*, speculative, high-volatile stocks), indicating a stronger beta anomaly among high turnover stocks. Finally, despite the perceived pricing anomaly (high-alpha, low-beta stocks), professional managers, however, have no incentives to engaging in arbitrage activities due to their mandate to beat a fixed benchmark, a phenomenon labelled as "*benchmark as limits to arbitrage*" by Baker *et al.* (2011).

It is worthwhile to spell out that the persistence of the low beta anomaly remains a mystery, as no consensus has been reached so far. We feel, instead of focusing on the cross-sectional pattern, a sharper test on these alternative explanations might be to examine their time-series predictions. Jylha (2018) provides some evidence in this regard, which supports the leverage-aversion theory (Frazzini & Pedersen 2014). However, margin constraints could only explain a small portion of the time variation of the low beta anomaly, and Jylha (2018) suggests to test other potential mechanisms, which are further tested in our work (see **Sections 4** and **5**).

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

3.1 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 convention (Han & Li 2017), 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 2x3 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 2x3 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 I recalculate the monthly returns of each fund.

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.

3.2 An "Inverted" SML Line in China vis-à-vis a "Flattened" SML line in the US

We start the empirical analysis by examining the (empirical) shape of the SML line at the firm level. Although either a flattened or an inverted SML line would lead to the low beta anomaly (*i.e.*, low beta stocks outperform high beta stocks on a risk-adjusted basis), the different shape would have completely different portfolio implications as noted in **section I**. That is, a flattened SML line 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 line implies a "different-return-and-similar-risk" anomaly which becomes exploitable for long-only investors (and long-and-short investors).

To detect the shape of the SML line 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.

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

The base-line 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). The strongly negative slope coefficient implies a downward sloping SML line. That is, the higher the market beta of a stock, the lower the expected return. High beta stocks underperform by low beta stocks on an *absolute* basis.

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.[1]

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

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

Note that the downward sloping SML line 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.

$$\begin{aligned} Ret_i - RF = a + b_1\beta_i + b_2 lnME_i + b_3 lnBTM_i + b_4 OP_i + b_5 INV_i \\ + b_6 RET_i^{MOM} + b_7 RET_i^{STREV} + \varepsilon_i \end{aligned}$$

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**, which follows the convention in the literature (Fama & French 2012, 2015).

Table 1 presents the multi-variation 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. Fama-MacBeth Regression at the Firm Level**]

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 line in China. Moreover, the

[1] Note the "flattened" CAPM line is not new for the US market (see, among others, Fama and French (1992) for various sample periods).

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. Of course, 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. However, a more relevant and urgent task is to understand the (possible) economic mechanisms that could contribute to the negatively sloped SML line in China. In fact, an "inverted" SML line represents a much bigger asset-pricing puzzle than a "flattened" SML line, because it indicates a negative price of risk in equilibrium which defies the traditional risk-based explanations of beta such as the CAPM model.

4. Theoretical Model: Investor Overconfidence and the SML Line

In this section, we develop a one-period CAPM model augmented with investor overconfidence to explain the beta anomaly, the negative relation between trading volume and the slope of the SML line, and the negative sloped SML line found in the Chinese equity market. It should be noted that the downward sloping SML line cannot be explained by 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 line, but cannot change the "sign" of the slope of the SML line (Black 1972; Jylha 2018). Apparently, other economic forces must be in play. Our behavioral framework could produce the downward sloping SML line observed in China. In our model, the representative agent is featured with some degree of overconfidence, so that she becomes overly confident about the signal of the stocks she receives.

The behavioral literature suggests that an overconfident agent tends to overestimate the informativeness of her signal (Scheinkman & Xiong 2003; Peng & Xiong 2006). As a result, the representative agent, who suffers from investor overconfidence, would underestimate return volatility when she learns from her signals about future asset returns. Assume there are N risky assets and one riskless asset with riskless rate r_f in the financial market. The investor's estimated variance-covariance matrix of the stock returns follows

$$\widehat{\mathbf{\Omega}} = \hat{\sigma}_m^2 \widehat{\boldsymbol{\beta}} \widehat{\boldsymbol{\beta}}', \qquad [4.1]$$

where $\widehat{\boldsymbol{\beta}}$ is the $N \times 1$ vector of the asset betas estimated by the investor with overconfidence, and $\hat{\sigma}_m^2$ is her estimated return volatility of the market portfolio. Due to overconfidence, $\hat{\sigma}_m^2$ is smaller than the true market volatility, σ_m^2, estimated by an outside econometrician with unbiased belief. For simplicity, we assume that the investor has correct expected returns, that is, her expected returns, $\boldsymbol{\mu}$, are the same as those estimated by an outside econometrician. According to Sharpe (1964) and Lintner (1965), stock returns satisfy a CAPM relationship:

$$\boldsymbol{\mu} - r_f \mathbf{1} = \widehat{\boldsymbol{\beta}} (\mu_m - r_f), \qquad [4.2]$$

where $\mathbf{1}$ is a $N \times 1$ vector of ones, and μ_m is the expected return of the market portfolio.

Following Stambaugh *et al.* (2015), we assume that the return volatility of the risky assets estimated by the outside econometrician who uses the true measure follows:

$$\boldsymbol{\Omega} = \sigma_m^2 \widehat{\boldsymbol{\beta}}\widehat{\boldsymbol{\beta}}' - \boldsymbol{\Sigma}, \qquad [4.3]$$

where $\boldsymbol{\Sigma}$ is a diagonal matrix with positive diagonal elements. According to Equation [4.3], the true volatilities are overly higher than those estimated by the irrational investor because $\sigma_m^2 > \hat{\sigma}_m^2$, and the true return correlations are also higher than those estimated by the overconfident investor. The latter is also consistent with Peng and Xiong (2006)[2] and can be seen as follows: The existence of the term "$\boldsymbol{\Sigma}$" makes the increases in variances (diagonal elements) under the true measure smaller than the increases in covariances (non-diagonal elements), implying that return correlations become lower under the true measure.[3] Therefore, the more overconfident the agent is, the lower $\hat{\sigma}_m^2$ is and the higher the diagonal elements of $\boldsymbol{\Sigma}$ are.

By definition, the assets' market beta estimated by the econometrician satisfy

$$\boldsymbol{\beta} = \frac{\boldsymbol{\Omega}\mathbf{x}_{\mathrm{m}}}{\mathbf{x}_m'\boldsymbol{\Omega}\mathbf{x}_{\mathrm{m}}}. \qquad [4.4]$$

By substituting Equation [4.3] into [4.4], and noting that $\mathbf{x}_m'\boldsymbol{\beta} = 1$, we obtain

$$\boldsymbol{\beta} = \frac{\sigma_m^2}{\sigma_m^2 - c}\widehat{\boldsymbol{\beta}} - \frac{\boldsymbol{\Sigma}\mathbf{x}_{\mathrm{m}}}{\sigma_m^2 - c} \qquad [4.5]$$

where $c = \mathbf{x}_m'\boldsymbol{\Sigma}\mathbf{x}_{\mathrm{m}} > 0$ increases with the degree of overconfidence. If follows from equations [4.2] and [4.5] that

$$\boldsymbol{\mu} - r_f\mathbf{1} = \boldsymbol{\alpha} + \frac{\sigma_m^2 - c}{\sigma_m^2}(\mu_m - r_f)\boldsymbol{\beta} \qquad [4.6]$$

where $\boldsymbol{\alpha} = \frac{\mu_m - r_f}{\sigma_m^2}\boldsymbol{\Sigma}\mathbf{x}_{\mathrm{m}}$ is the vector of the risk-adjusted returns of the risky assets. Equation [1.6] shows that CAPM does not hold under the econometrician's measure. In fact, the market portfolio is determined by the investors whose estimation of stock returns are different from those of the econometrician. As a result, although the market portfolio is efficient under the investor's measure, it can by inefficient under the econometrician's measure.[4] Because $\frac{\sigma_m^2 - c}{\sigma_m^2} < 1$, Equation [4.6] shows that

[2] Peng and Xiong (2006) show that advancement in information technology reduces return correlations relative to fundamental correlations. Investor overconfidence has qualitatively similar effects on returns. Therefore, overconfidence reduces return correlations in the sense that the correlations estimated by the outside econometrician who has rational belief should be higher that those estimated by the overconfident investor.
[3] Notice that the covariance between two returns equals the product of correlation and the standard deviations of the two returns.
[4] 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),

overconfidence reduces the slope of the security market line. Especially, the SML line could have a negative slope, if $> \sigma_m^2$. Therefore, we have the following proposition.

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.*

Our static economy can be easily extended to a dynamic overlapping-generations (OLG) one as in Frazzini and Pedersen (2014), in which the dynamic setting allows us to define trading volume. In this case, the market-wide trading volume is measured by the sum of the trading volumes of all individual stocks, which are defined as the sum of the absolute value of the change in investors' demand (Wang 1994; Banerjee & Kremer 2010). An increase in the degree of overconfidence decreases $\hat{\sigma}_m^2$ and hence increases the total demand and trading volume (because trading volume decreases with volatilities in the mean-variance framework of CAPM). This, together with **Proposition 1.1**, leads to the following proposition.

Proposition 1.2. *The slope of SML line estimated by an outside econometrician has a negative relationship with trading volume.*

One thing subtle is that Equation [4.6] indicates that an increase in the degree of overconfidence increases the diagonal elements of $\mathbf{\Sigma}$ and hence increases a security's alpha. In other words, overconfidence would have a strong impact on both the security's alpha and beta, but in completely opposite directions. This also implies that increased overconfidence, manifested by extremely high trading volume, would influence both the intercept and slope of the SML line, which we test in the next section.

We are aware a number of behavioural mechanisms exist in the literature, which are able to explain the low-beta anomaly in the cross section. We feel that the investor overconfidence mechanism is somehow being overlooked. In fact, our overconfidence-related model is 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 line in China. Disagreement (*i.e.*, heterogeneous beliefs) alone also cannot explain the negative sloped SML line, because the equilibrium price is a weighted average of different beliefs with wealth-dependent weights.

In our model, we have assumed that the overconfident investor still forms the correct estimate of the mean returns of the risky assets, this conservative assumption 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

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 [4.6] 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.

overconfidence, alone, could explain the time-series and cross-sectional patterns regarding the low-beta anomaly.

5. Time-series Evidence

5.1. 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 security market line (Jylha 2018). In the first step, we perform the month-by-month Fama-MacBeth cross-sectional regression (as in **subsection 3.2**) by regressing the excess returns on the CAPM betas to obtain the time series of the intercept and slope of the SML line.

$$Ret_{it} - RF_t = Intercept_t + Slope_t \beta_{it} + \varepsilon_{it}$$

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 line 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 trading volume. The turnover ratio is constructed as the value-weighted average across all firms in the market. In addition, we also include a number of standard control variables.

$$Intercept_t = a_1 + b_1 Turnover_{t-1} + c_1 RMRF_t + \boldsymbol{d}_1' \boldsymbol{X}_t + u_{1,t}$$

and

$$Slope_t = a_2 + b_2 Turnover_{t-1} + c_2 RMRF_t + \boldsymbol{d}_2' \boldsymbol{X}_t + u_{2,t}$$

Following Jylha (2018), our control variables include the market return ($RMRF$), the lagged market volatility (defined as the standard deviation of the daily market returns within the prior month). We also use the *ex ante* beta spread ($\beta_H - \beta_L$) defined in the BAB portfolio to proxy for the overall margin status (*i.e.*, funding liquidity). This is motivated by the fact that other more conventional measures of margin constraints (such as SHIBOR rate in China) is only available for a small portion of our sample period (*i.e.*, from 2009 onwards). In the framework of Frazzini and Pedersen (2014), a smaller beta spread indicates tightened margin constraints (*i.e.*, beta compression). In reality, a widening of the beta spread could also be triggered by other macroeconomic reasons. Therefore, the slope coefficient on the beta spread might overestimates the true impact of margin constraints. We are aware that the time variation of market-wide trading volume could also be partially due to rational adjustment to the market-wide information. To purge the rational response of trading volume to the shifts in market conditions, we, therefore, also include the country-specific economic policy uncertainty index (EPU) for China, obtained from Baker *et al.* (2016), to control for the time variation of the market-wide informational status. We use either the change in EPU index or lagged EPU value as alternative proxies for the prevailing market-wide uncertainty. The additional control variables we include are the Fama-French size and value factors, and Carhart's momentum factor.

5.2. Trading Volume and the Shape of the SML Line

Table 2 provides the estimation results for the second-stage time-series regression of the intercept and slope of time SML line. A number of salient features emerge from the table:

First, we find the factor loadings on the *ex ante* beta spread are significant for both the intercept and the slope of the SML line in China (see column 6), confirming that margin or leverage constraints explains partially the time variation of the low beta anomaly which is consistent with the findings of Jylha (2018).

Second, 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 line in China, after accounting for all other control variables (column 1 to 6). Given that we have accounted for the rational changes in the SML line by including the EPU index, market volatility, and Fama-French risk factors, the loadings on turnover ratio lend strong supports to **proposition 1.1. and 1.2.** in our theoretical model. Moreover, the different signs of the loadings on turnover ratio for the zero-beta portfolio and the unit-beta portfolio reinforces our conjecture that shifts in investor overconfidence would impact the intercept and slope of the SML line in opposite directions. To be specific, following high market-wide trading volume, the slope of the SML line becomes more downward sloping, indicating a stronger (conditional) low-beta anomaly (*i.e.*, low-beta stocks outperform high-beta ones). In contrast, the expected return of the zero-beta portfolio would adjust upwards subsequent to the increase of trading volume.

Third, 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 7.28% percent for the zero-cost unit-beta portfolio (*i.e.*, the slope of the SML line), and an upward adjustment of 11.58% percent for the zero-cost zero-beta portfolio (*i.e.*, the intercept of the SML line). In comparison, the economic consequence for a one-standard-deviation shock in margin conditions (*i.e.*, the beta spread) would only bring an upward adjustment of 1.59% percent for the unit-beta portfolio, and a downward adjustment of 2.51% percent for the zero-beta portfolio, respectively.[5] From the economic perspective, it seems that trading volume is a much stronger time-series determinant of the low-beta anomaly than margin conditions in China.

To sum up, following a broad wave of investor optimism, manifested by market-wide trading volume, relatively risky assets (*i.e.*, high-beta stocks) underperform relatively safe assets (*i.e.*, low-beta stocks), implying a more "inverted" SML line. In other words, the price of risk becomes more negative subsequent to extremely high trading volume.

[**Insert Table 2 here**]

6. Cross-sectional Evidence

[5] To facilitate comparison, we have standardized the turnover ratio and beta spread (*i.e.*, zero mean and unit variation) before putting them into the regression model.

6.1. Betting Against Beta

Motivated by the “flattened” CAPM line in the US, Frazzini and Pedersen (2014) designed a market-neutral betting against beta strategy (BAB), 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 line in China should also 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 portfolio weights. Analytically, the rank-based weighting scheme for the low (high) beta portfolio is expressed as follows:

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

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.

$$BAB = \frac{1}{\beta_L} R^{LOW} - \frac{1}{\beta_H} R^{HIGH}$$

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 line 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 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 either constrained in taking short positions due to mandate or the high costs related to shorting.

[**Insert Table 3 of BAB and its components**]

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). 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 implies 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. 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.

6.2. Time-series Spanning Tests

In the prior subsections, 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 non-negative position of the risky assets. However, traditional risk factors are all pure long-and-short portfolios (*i.e.*, a zero-cost position). 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.[6]

Similarly, panel B of **table 4** present the results with the unlevered equal-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 of Time-series Spanning Tests**]

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

[6] 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.

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-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 of Stock Feature of the Decile Portfolios**]

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.[7]

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 also has the stocks which have the best performance over the prior month, which might lead to strong return reversal over a short period.

[7] 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.

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 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 (over the risk-free rate) 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 provide more direct evidence of the low beta effect: The low beta portfolios tend to outperform the high beta counterparties 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**). Moreover, 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.

[**Insert Table 6 of the Beta-sorted Decile Portfolios**]

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.

7. Robustness Tests and Further Analyses

7.1. Re-examine the Shape of the CAPM line in China

In this subsection, we test the robustness of the "downward sloping" shape of the CAPM line in China. Liu *et al.* (2018) argue that the low beta anomaly is mainly driven by sentiment-induced mispricing. It is well known that investor sentiment is mainly a size story (Lee *et al.* 1991) and it is particularly the case in China as retail investors prefer small-sized stocks (Han & Li 2017). Therefore, 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 10 percent of the total market capitalization in China.

Table 7 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. However, the magnitude of the beta coefficient becomes smaller as compared to the results in **table 1**. The beta coefficient also gets less significant compared to the *t*-statistics with the full sample in **table 1**. These changes provide indirect evidence that the low beta anomaly is somehow related to investor sentiment.

The bottom line, however, is that there still exists a striking downward sloping SML in the subsample that excluding the micro-cap stocks. Moreover, 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. Overall, the low beta anomaly seems a full market phenomenon in China rather than a sub-market one.

[**Insert Table 7. Fama-MacBeth Regression at the Firm Level**]

7.2. The "Horse Race"

Multiple competing, risk-based or behavioural explanations (see **section 2**) 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 "destroys" cross-sectional information and do not increase the precision of the coefficient estimates (Ang *et al.* 2008). Second, the aggregation also artificially increases the correlation between firm characteristics and the test variable (Hou & Loh 2016). Third, the pricing pattern of the test variable (*i.e.*, beta) might not stems from the part that is explained by the firm characteristics, a possibility that is cautioned by Hou and Loh (2016).

Therefore, we differ from all the concurrent study on the low beta anomaly that focused on portfolio evidence by adopting a novel decomposition approach proposed in Hou and Loh (2016) to evaluate the competing explanations on the low beta anomaly.

The Hou and Loh (2016)'s "horse race" is performed at the firm level. It uses the DGTW characteristics-adjusted returns as the dependent variable for the Fama-MacBeth regression and the decomposition exercise. In the first stage, period-by-period Fama-MacBeth cross-sectional regressions are performed which regresses the characteristics-adjusted returns on the market betas to obtain the time-series average of the slope coefficients on betas. 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, 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 step, the average beta coefficient obtained in the first stage is further decomposed into two orthogonal components based on the property of linearity of covariance.

Table 8 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. Based on that, Fama and French (2015) augment the Fama-French three-factor model with the profitability and investment factors to better capture the dispersion of the cross-sectional returns. For the risk-based explanation 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 cross-sectional slope coefficient on beta into the explained and unexplained portions, the result of the decomposition is disappointing. The explained portion due to OP explains virtually zero percent of the low beta anomaly. It seems that the low beta anomaly is driven 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 8**) 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 characteristics. Similarly, we find no evidence for firm investment (INV) to be the driver of the low beta anomaly, as the decomposition exercise demonstrate that the "explained" slope coefficient is 0.05 and the explained portion is -4 percent and not statistically significant (see column 2).

The short-term return reversal ($\mathrm{RET}^{\mathrm{STREV}}$) is another pervasive phenomenon in the financial markets. The possibility that high beta stocks are also the stocks having 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 also does not receive too much support by the evidence in the decomposition exercise. The explained proportion due to $\mathrm{RET}^{\mathrm{STREV}}$ is only around 4 percentages, and it is not statistically significant at all. The low beta anomaly is driven by the part that is orthogonal to the short-term return reversal measure. In other words, the short-term reversal variable is not a viable solution to the low beta anomaly at all.

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 percent, which is statistically significant at the 1% level.

The fifth column uses the Harvey and Siddique (2000) coskewness measure (SSKEW) in explaining the low-beta anomaly. 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 any support in our dataset, as 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, as the explained portion by the coskewness measure is -3.0%. In other words, the coskewness feature does not explain the beta anomaly at all.

The next column investigates the idiosyncratic skewness (ISKEW) for the low-beta phenomenon. 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 too much power in explaining the return-beta pattern, as the idiosyncratic-related component only contributes to 4% of the negative slope coefficient on betas, and this proportion is statistically significant.

The next candidate variable is the Ang *et al.* (2006) idiosyncratic volatility (IVOL) measure. 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. Moreover, they further attribute the beta-related mispricing to investor sentiment. It should be noted, however, that an alternative view is to treat IVOL as the volatility version of the lottery-demand measure. For example, Bali *et al.* (2011) argues that stocks with high idiosyncratic volatility (IVOL) are generally perceived as lottery stocks. 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 percentages, which is significant at the 5% level.

It should be noted that the strong explaining power from idiosyncratic volatility and MAX5 in explaining the beta anomaly might simply be mechanical (Hou & Loh 2016). By construction, beta is a measure of risk that is highly correlated with a stock's 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.

Moving across the table, the next candidate variable is the price level (PRC), defined as the closing price at the prior month. 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**. The decomposition results, however, suggest the other way around, as the explained portion by the price level is approximately -9.0% and it is insignificant as well. In other words, the price level does not explain the inverse relation between returns and market beta.

Last but not least, we use the firm-level turnover ratio (TURN) as the candidate variable to explain the low beta effect. In **table 6**, there exists 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 this conjecture. The explained proportion by TURN amounts to 122 percentages, which is statistically significant at the 5% level. In other words, the beta pricing pattern is almost completely captured by the turnover ratio.[8] It should be pointed out from the outset that the firm-level turnover ratio could serve as a "catch-all" behavioural variable for investor overconfidence. In the behavioural literature, speculative stocks tend to have high trading volumes (*i.e.*, turnover) and lower subsequent returns (Baker & Wurgler 2007). Moreover, high volume also indicates that these are the stocks receiving the most investor attention in the cross section, a symptom of investor overconfidence or overreaction (Baker *et al.* 2011). High volume stocks also enjoy greater price disagreement (Miller 1977) and are, in general, difficult to arbitrage (Chou *et al.* 2013). Besides, extremely high turnover ratio could also serve as a direct measure of lottery demand, as retail investors engage in correlated trading for these stocks (Kumar & Lee 2006). All of the behavioural mechanisms dictate that stocks with high turnover ratio (high beta stocks) would have lower subsequent returns. While some might argue that high volume stocks tend to have lower expected returns for rational or quasi-rational reasons (*i.e.*, market frictions or illiquidity). 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 percentages, making the market friction less of a concern for investors. Second, popular friction measures such as the Hou and Moskowitz (2005) price delay measure and the Amihud (2002) illiquidity measure explain less than 10% of the slope coefficient in beta (unreported for brevity purpose). Therefore, the success of turnover ratio in capturing the beta pricing pattern lends more supports to our overconfidence-based behavioural mechanism in resolving the low beta anomaly.

[**Insert Table 8 of the Decomposition**]

To sum up, by cross-linking the portfolio evidence in **table 6** and the "horse race" of the firm-level decomposition exercise in **table 8**, 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 maximum five

[8] 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.

daily returns in prior month, and the idiosyncratic variables all seem to be able to capture the pricing power of beta in the cross section of stock returns. Therefore, the low beta anomaly in China seems to be more in line with the behavioural mechanisms such as lottery demand and investor overconfidence (Baker *et al.* 2011; Bali *et al.* 2017; Liu *et al.* 2018), but in contradiction to the risk-based mechanisms such as in Schneider *et al.* (2015).

7.3. 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 beta-sorted quintile portfolio 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 9 of the Bivariate sorted portfolios**]

Panel A of Table 9 reports the performance of the characteristics-controlled beta-sorted quintile portfolios and the associated high-minus-low beta portfolios. For brevity purpose, only the alphas of the Fama-French five-factor model 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). As it stands, after controlling for the turnover effect, there no long exists a low beta anomaly. On the contrary, stock beta becomes a positive return predictor in the cross section: 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 return differential between Q5 and Q1 portfolios also becomes positive, though it is not statistically significant.

The fact that beta flips its sign in predicting cross-sectional stock returns after controlling for the turnover ratio 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 sequentially sorted into five quintile portfolios based on the three behavioural characteristics (*i.e.*, IVOL, MAX5, and TURN) in ascending orders. The 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 9** 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 alpha of -0.65 percentages and is also statistically significant at the 1% level. The high-minus-low IVOL portfolio yields a negative alpha of -1.91 percentages 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 MAX5-sorted (TURN-sorted) quintile portfolios that control for the beta effect. The Q1 MAX5-sorted (TURN-sorted) quintile portfolio earns an impressive positive alpha of 1.09 (0.99) percentages 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) percentages with a t-statistics of -5.56 (-5.96). Compared to the beta-sorted quintile portfolio which controls for MAX5 (TURN), the most remarkable features are: First, the Q5 quintile portfolio generally underperforms on a risk-adjusted basis, which is consistent with the lottery demand explanation or, more general, the behavioural-based explanation that lottery investors push up the price of lottery stocks, which generates lower returns on a risk-adjusted basis. Second, the zero cost, high-minus-low portfolio also exhibits much larger return differential when sorted on "pure" behavioural measures than stock beta.

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 both on an absolute basis (and 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, I 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 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 good-performing 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 of the Mutual Funds**]

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 vis-à-vis the "flattened" CAPM line in the US. The *mini* cross-country comparison indicates that the low beta anomaly is much more pronounced in China than in the US, which is demonstrated in the BAB strategies over the same sample period.

Unfortunately, the downward sloping SML line in China cannot be explained by existing theories of low-beta anomaly which generally resorts to some sort of market constraints. We, therefore, provide a modified CAPM model augmented with investor overconfidence to the puzzling low-beta anomaly in China. The key model prediction suggests that a negative relationship between trading volume and the slope of the SML line. In the time-series dimension, we provide compelling evidence that the slope of the SML line becomes more "inverted" subsequent to increased trading volume, which confirms our model prediction. Note this negative relationship would not exist for any rational based asset pricing models. In the cross section, after a comprehensive "horse race", we find that the low beta anomaly seems to be fully captured by the trading volume (*i.e.*, the turnover ratio). In fact, after controlling for stock turnover ratio, there is no longer a low-beta effect, as high beta portfolios generate higher risk-adjusted returns than low beta portfolios (see the bivariate portfolio sorts in Section 7.3).

Finally, a downward sloping SML line 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 and Newey–West adjusted *t*-statistics (in *italic*) 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**	$\mathbf{RET^{MOM}}$	$\mathbf{RET^{STREV}}$	$\boldsymbol{Adj.R^2}$	**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 line on the (possible) economic determinants. Turnover(-1) is the lagged value-weighted turnover ratio across all firms in the prior month. Beta Spread is the *ex ante* beta differential between high-beta and low-beta portfolios in the BAB strategy. EPU(-1) and ΔEPU are the lagged economic uncertainty index and the first-order difference of the EPU index, respectively. Volatility(-1) is the lagged return volatility, defined as the standard deviation of the market returns in prior month. RMRF, SMB, HML, and MOM are the market, size, value, and momentum factors, respectively. Newey–West adjusted t-statistics are reported in *italic*. $Adj.R^2$ is the adjusted R-square, and Obs. is the number of observations. The sample period is between July 1996 and December 2016.

	Intercept						**Slope**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Const.	-2.04	-1.82	0.95	2.87	4.01	6.97	1.20	1.47	-1.71	-2.67	-3.89	-5.45
	-1.34	*-1.42*	*0.49*	*1.29*	*1.40*	*2.23*	*1.04*	*1.16*	*-0.99*	*-1.30*	*-1.48*	*-2.39*
Turnover(-1)	8.23	7.44	8.84	7.56	7.84	11.58	-4.91	-5.87	-7.47	-6.86	-7.16	-7.28
	3.89	*4.57*	*5.74*	*5.24*	*6.33*	*6.82*	*-4.29*	*-3.82*	*-5.10*	*-5.28*	*-6.38*	*-6.29*
ΔEPU	-0.58	0.18	0.08	0.28	-0.14	-0.88	-1.31	-0.40	-0.29	-0.31	0.13	0.27
	-0.45	*0.16*	*0.08*	*0.26*	*-0.11*	*-0.45*	*-1.23*	*-0.37*	*-0.27*	*-0.31*	*0.11*	*0.27*
EPU(-1)					-0.01	-0.01					0.01	0.01
					-0.94	*-0.41*					*1.11*	*1.36*
Beta Spread						-2.51						1.59
						-2.74						*2.43*
RMRF		0.48	0.48	0.57	0.56	0.04		0.58	0.58	0.44	0.46	0.80
		2.69	*2.73*	*4.72*	*4.89*	*0.20*		*3.40*	*3.46*	*4.01*	*4.32*	*5.53*
Volatility(-1)			-2.47	-2.36	-2.39	-6.26			2.83	2.03	2.06	4.02
			-1.76	*-1.82*	*-1.81*	*-3.45*			*2.43*	*1.63*	*1.62*	*3.16*
SMB				-0.55	-0.55	3.63				1.20	1.20	0.60
				-1.80	*-1.80*	*13.47*				*5.01*	*5.00*	*3.21*
HML				-1.39	-1.38	0.40				1.33	1.323	0.459
				-4.16	*-4.09*	*1.19*				*4.92*	*4.83*	*2.22*
MOM				-0.92	-0.93	-0.72				0.73	0.74	0.436

				-2.07	*-2.09*	*-1.24*				*1.84*	*1.86*	*1.07*
$Adj.R^2$	0.07	0.13	0.14	0.29	0.29	0.54	0.02	0.12	0.13	0.34	0.34	0.35
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 are reported in *italic*. $Adj.R^2$ 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	0.1834	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	0.9323	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	0.9713	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) portfolio, the unlevered betting against portfolio ($BAB^{UNLEVER}$), and the equal-weighted low-minus-high beta portfolio (BAB^{EW}) as the explanatory variable, respectively. The dependent variables, RMRF, SMB, HML, RMW, and CMA are the market, size, value, profitability, and investment factors, respectively. Newey–West adjusted *t*-statistics are reported in *italic*. 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 (N_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
N_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 are reported in *italic* 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. 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 $t-1$. $\mathrm{RET}^{\mathrm{MOM}}$ 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 and Newey–West adjusted *t*-statistics (in *italic*) 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	$\mathrm{RET}^{\mathrm{MOM}}$	$\mathrm{RET}^{\mathrm{STREV}}$	$Adj.R^2$	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 8. Decomposing the Low Beta Anomaly: Horse Race

The table reports the firm-level Fama-MacBeth cross-sectional regressions over the periods between July 1996 and December 2016. 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 (second row) and the Newey-West *t*-statistics (third row) in *italic*. In the second stage, the negative relation between the characteristics-adjusted returns and firm betas is decomposed into a component which is related to a candidate variable and a residual component. The candidate variables are the ratio of operational profits and book equity (OP), the growth of total assets (INV), the short-term return reversal defined as the prior-month return ($\mathrm{RET}^{\mathrm{STREV}}$), the average of the top 5 daily returns over the prior month (MAX5), systematic skewness (SSKEW), idiosyncratic skewness (ISKEW), idiosyncratic volatility (IVOL), the price level of the stocks (PRC), and average turnover ratio (TURN). Explained is the part of the first-stage slope coefficient explained by the candidate variable. Unexplained is the unexplained part of the slope coefficient. The relative proportion of explained and unexplained part is also reported, together with their *t*-statistics. Total is the sum of the coefficients of the explained and unexplained components. All explanatory variables are winsorized at the 0.5 and 99.5% level. The sample period is between July 1996 and December 2016.

	OP	INV	$\mathrm{RET}^{\mathrm{STREV}}$	MAX5	SSKEW	ISSKEW	IVOL	PRC	TURN
				Fama-MacBeth Cross-sectional Regression					
Const.	1.60	1.52	1.55	1.55	1.55	1.55	1.50	1.55	1.14
	2.57	*2.44*	*2.49*	*2.49*	*2.49*	*2.49*	*2.40*	*2.49*	*1.98*
	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
	-2.52	*-2.38*	*-2.43*	*-2.43*	*-2.43*	*-2.43*	*-2.33*	*-2.43*	*-1.99*
	-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
$Adj.R^2$	0.0105	0.0111	0.0111	0.0111	0.0111	0.0111	0.0111	0.0111	0.0103
				The Decomposition of the Slope Coefficient					
Explained	-0.01	0.05	-0.05	-1.43	0.05	-0.06	-1.16	0.12	-1.35
proportion	0.00	-0.04	0.04	**0.98**	-0.03	0.04	**0.83**	-0.09	**1.22**
t-stat	*0.07*	*-0.71*	*0.44*	*2.82*	*-0.41*	*0.90*	*2.55*	*-0.85*	*2.11*
Unexplained	-1.50	-1.48	-1.39	-0.02	-1.50	-1.39	-0.23	-1.57	0.25
proportion	1.00	1.04	0.96	0.02	1.03	0.96	0.17	1.09	-0.22
t-stat	*14.24*	*20.88*	*11.36*	*0.05*	*12.74*	*20.26*	*0.51*	*10.77*	*-0.39*

Total	-1.50	-1.43	-1.45	-1.45	-1.45	-1.45	-1.39	-1.45	-1.10
proportion	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 9. 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). 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 are reported in *italic* below the coefficients. The sample period is between July 1996 and December 2016.

	Panel A: Second Dimension = Beta							**Panel B: First Dimension = Beta**					
FF5	**Q1 = Low**	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q5 - Q1**	**FF5**	**Q1 = Low**	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q5 - Q1**
IVOL-Beta	0.76	0.28	0.19	0.22	0.05	-0.71	Beta-IVOL	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-Beta	0.66	0.21	0.20	0.28	0.22	-0.43	Beta-MAX5	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-Beta	0.07	-0.01	0.23	0.20	0.27	0.20	Beta-TURN	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 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 are reported in *italic*. 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*
β^{RMRF}	-1.30	1.01	0.59	-0.33	
	-1.36	*1.64*	*0.68*	*-0.32*	
β^{SMB}		1.08	0.74	0.58	0.63
		5.06	*2.31*	*1.85*	*3.24*
β^{HML}		0.87	0.95	0.97	0.98
		4.46	*4.00*	*4.87*	*4.97*
β^{RMW}			0.54	0.18	0.19
			2.25	*1.20*	*1.25*
β^{CMA}			-0.37	0.10	0.08
			-1.93	*0.38*	*0.38*
β^{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*
β^{RMRF}	-1.40	0.96	0.57	-0.28	
	-1.41	*1.56*	*0.66*	*-0.27*	
β^{SMB}		1.10	0.75	0.60	0.64
		5.12	*2.37*	*1.84*	*3.16*
β^{HML}		0.88	0.95	0.97	0.98
		4.57	*4.01*	*4.74*	*4.86*
β^{RMW}			0.52	0.25	0.25
			2.26	*1.52*	*1.53*
β^{CMA}			-0.35	0.04	0.02
			-1.82	*0.16*	*0.12*
β^{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, $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1 + r_{t+k}^{i})$, 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 β_i^{TS} toward the cross-sectional mean β^{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).

$\mathrm{RET}^{\mathrm{MOM}}$	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.
$\mathrm{RET}^{\mathrm{STREV}}$	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.
ILLIQ	Amihud illiquidity ratio, defined as the as the annual average of the ratio of absolute return and the dollar trading volume (Amihud 2002).

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 and Newey–West adjusted *t*-statistics (in *italic*) 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**	$\mathbf{RET^{MOM}}$	$\mathbf{RET^{STREV}}$	$\boldsymbol{Adj.R^2}$	**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 are reported in *italic*. $Adj. R^2$ 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**	$\boldsymbol{Adj. R^2}$	**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*		

Reference

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The Cross-section of volatility and expected returns. The Journal of Finance 61, 259-299

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: International and further U.S. evidence. Journal of Financial Economics 91, 1-23

Ang, A., Liu, J., Schwarz, K., 2008. Using Individual Stocks or Portfolios in Tests of Factor Models. SSRN Electronic Journal

Asness, C.S., Frazzini, A., Pedersen, L.H., 2012. Leverage aversion and risk parity. Financial Analysts Journal 68, 47-59

Auer, B.R., Schuhmacher, F., 2015. Liquid betting against beta in dow jones industrial average stocks. Financial Analysts Journal 71, 30-43

Baker, M., Bradley, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. Financial Analysts Journal 67, 40-54

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. The Journal of Economic Perspectives 21, 129-151

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics 131, 1593-1636

Bali, T.G., Brown, S., Murray, S., Tang, Y., 2017. A lottery demand-based explanation of the beta anomaly. Journal of Financial and Quantitative Analysis (Forthcoming)

Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427-446

Banerjee, S., Kremer, I., 2010. Disagreement and learning: Dynamic patterns of trade. The Journal of Finance 65, 1269-1302

Barber, B.M., Odean, T., 2000. Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. The Journal of Finance 55, 773-806

Barberis, N., Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. The American Economic Review 98, 2066-2100

Black, F., 1972. Capital market equilibrium with restricted borrowing. The Journal of Business 45, 444-455

Blitz, D., Vidojevic, M., 2017. The profitability of low-volatility. Journal of Empirical Finance 43, 33-42

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57-82

Chou, P.-H., Huang, T.-Y., Yang, H.-J., 2013. Arbitrage risk and the turnover anomaly. Journal of Banking & Finance 37, 4172-4182

Daniel, K., Titman, S., 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. Journal of Finance 52, 1-33

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. The Journal of Finance 47, 427-465

Fama, E.F., French, K.R., 2006. The Value Premium and the CAPM. Journal of Finance 61, 2163–2185

Fama, E.F., French, K.R., 2012. Size, value, and momentum in international stock returns. Journal of Financial Economics 105, 457-472

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1-22

Fama, E.F., French, K.R., 2017. International tests of a five-factor asset pricing model. Journal of Financial Economics 123, 441-463

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. The Journal of Political Economy, 607-636
Frazzini, A., Pedersen, L.H., 2014. Betting against beta. Journal of Financial Economics 111, 1-25
Friend, I., Blume, M., 1970. Measurement of Portfolio Performance Under Uncertainty. American Economic Review 60, 561-575
Gibbons, M.R., 1982. Multivariate tests of financial models: A new approach. Journal of financial economics 10, 3-27
Gibbons, M.R., Ross, S.A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica: Journal of the Econometric Society, 1121-1152
Han, X., Li, Y., 2017. Can investor sentiment be a momentum time-series predictor? Evidence from China. Journal of Empirical Finance 42, 212-239
Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. The Journal of Finance 55, 1263-1295
Haugen, R.A., Heins, A.J., 1975. Risk and the rate of return on financial assets: Some old wine in new bottles. Journal of Financial and Quantitative Analysis 10, 775-784
Hou, K., Loh, R.K., 2016. Have we solved the idiosyncratic volatility puzzle? Journal of Financial Economics 121, 167-194
Hou, K., Moskowitz, T.J., 2005. Market frictions, price delay, and the cross-section of expected returns. The Review of Financial Studies 18, 981-1020
Jagannathan, R., Ma, T., 2003. Risk reduction in large portfolios: Why imposing the wrong constraints helps. The Journal of Finance 58, 1651-1683
Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance 48, 65-91
Jobson, J.D., Korkie, B., 1982. Potential performance and tests of portfolio efficiency. Journal of Financial Economics 10, 433-466
Jylha, P., 2018. Margin Requirements and the Security Market Line. The Journal of Finance (Forthcoming) 0
Kandel, S., Stambaugh, R.F., 1987. On correlations and inferences about mean-variance efficiency. Journal of Financial Economics 18, 61-90
Kraus, A., Litzenberger, R.H., 1976. Skewness preference and the valuation of risk assets. The Journal of Finance 31, 1085-1100
Kumar, A., 2009. Who gambles in the stock market? The Journal of Finance 64, 1889-1933
Kumar, A., Lee, C.M.C., 2006. Retail investor sentiment and return comovements. The Journal of Finance 61, 2451-2486
Lee, C.M.C., Shleifer, A., Thaler, R.H., 1991. Investor Sentiment and the Closed-End Fund Puzzle. The Journal of Finance 46, 75-109
Levy, M., Roll, R., 2010. The Market Portfolio May Be Mean/Variance Efficient After All: The Market Portfolio. The Review of Financial Studies 23, 2464-2491
Li, X., Sullivan, R.N., Garcíafeijóo, L., 2016. The Low-Volatility Anomaly: Market Evidence on Systematic Risk versus Mispricing. Financial Analysts Journal 72, 1-12
Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. The review of economics and statistics, 13-37
Liu, J., Stambaugh, R.F., Yuan, Y., 2018. Absolving Beta of Volatility's Effects. Journal of Financial Economics 128, 1-15
MacKinlay, A.C., Richardson, M.P., 1991. Using generalized method of moments to test mean‐variance efficiency. The Journal of Finance 46, 511-527
Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of Finance 32, 1151-1168
Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1-28

Odean, T., 1999. Do investors trade too much? American economic review 89, 1279-1298
Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80, 563-602
Roll, R., 1977. A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. Journal of financial economics 4, 129-176
Ross, S.A., 1977. The capital asset pricing model (CAPM), short‐sale restrictions and related issues. The Journal of Finance 32, 177-183
Scheinkman, J.A., Xiong, W., 2003. Overconfidence and Speculative Bubbles. Journal of political economy 111, 1183-1220
Schneider, P., Wagner, C., Zechner, J., 2015. Low Risk Anomalies? CFS Working Paper
Shanken, J., 1985. Multivariate tests of the zero-beta CAPM. Journal of financial economics 14, 327-348
Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance 19, 425-442
Stambaugh, R.F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. The Journal of Finance 70, 1903-1948
Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Review of Financial Studies 19, 1531-1565
Vasicek, O.A., 1973. A Note on Using Cross‐sectional Information in Bayesian Estimation of Security Betas. The Journal of Finance 28, 1233-1239
Wang, J., 1994. A model of competitive stock trading volume. Journal of political Economy 102, 127-168