A Cross-Sectional Decomposition of Firms' Market Betas*

Hitesh Doshi Kris Jacobs
University of Houston

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Abstract

We propose a new empirical framework for cross-sectional asset pricing. The framework generalizes and nests the CAPM. We decompose the firm's traditional CAPM market beta in two components: a negative market beta, which contains the negative correlations between the return of the firm and other firms, and a positive market beta, which contains the positive correlations. The sum of the positive and negative betas is the total market beta, and we expect all three betas to have a positive price of risk. We find that the negative beta, which is the beta component that provides a hedge against the overall market, carries a statistically significant and economically large risk premium of 7.44% per annum. Like the total market beta, the positive beta is not statistically or economically significant. The information contained in the proposed negative and positive betas is economically and intuitively very different from the upside and downside betas in Ang et al. (2006a) and the semibetas of Bollerslev et al. (2022). The estimated price of risk associated with the negative beta is also robust to including other factors and characteristics used in the cross-sectional literature.

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1 Introduction

The study of determinants of cross-sectional return differences between stocks and other securities is one of the most important research areas in finance. While the literature has proposed a bewildering array of pricing factors and characteristics to explain these differences, the Capital Asset Pricing Model (CAPM) continues to play an important role in this literature. The literature has long considered various interesting generalizations that nest the CAPM. One approach, originating with Kraus and Litzenberger (1976), considers comovements with higher moments of market returns.[1] Ang et al. (2006b) instead propose a decomposition of market beta and emphasize the role of downside market beta, which assumes that investors are averse to volatility when it leads to losses.[2] Along similar lines, Bollerslev et al. (2022) propose semibetas that further disentangle good and bad downside risks.[3]

This paper proposes an alternative decomposition of the market beta. At first blush this decomposition may seem similar to the one in Ang et al. (2006b) and Bollerslev et al. (2022), but it is radically different. We decompose the traditional market beta in two components: the negative market beta contains the negative correlations between the return of the firm and other firms, while the positive market beta contains the positive correlations. By construction the sum of these two betas is the traditional market beta. Like the traditional market beta, we expect both the negative and the positive market beta to carry a positive price of risk.

Our empirical findings show that like the total market beta, the positive market beta is not statistically or economically significant. However, we find that the negative market beta carries a statistically significant and economically large risk premium of more than

[1] See for instance Harvey and Siddique (2000), Dittmar (2002), Christoffersen et al. (2021).
[2] See Atilgan et al. (2019) and Levi and Welch (2020) for other results on downside risk.
[3] See Bollerslev et al. (2020) and Bollerslev et al. (2024) for additional results on the pricing of semibetas.

seven percent per annum. Intuitively, the negative market beta for firm i is the component that provides a hedge against the movements of the overall market. It can be thought of as using the traditional intuition for the CAPM that values stocks which provide a hedge against market fluctuations. While in the CAPM implementation, the building block to construct the hedge is the covariation between stock i and the market at a given time t, in our implementation the building block is the co-variation between stock i and another stock j at time t.

We verify that this empirical finding on the pricing of the negative market beta is very robust. The statistical and economic significance of the negative beta remains when including the upside and downside betas in Ang et al. (2006a) and the semibetas of Bollerslev et al. (2022). We show that its economic and statistical significance also remains in the presence of a wide variety of cross-sectional predictors suggested by the existing literature, including size, book-to-market, momentum, realized variance, idiosyncratic volatility, reversal, illiquidity, turnover, and volume. The alpha associated with a factor based on the long-short return on the negative market beta is economically large and is robust to including the factors from well-known factor models. However, while negative market beta is distinct from these existing characteristics and factors, it is related to several cross-sectional predictors and anomalies. Firms with low negative market beta are more illiquid and smaller. They exhibit greater momentum and their returns are more volatile. Because negative market beta is well-motivated by economic intuition and theory, it can be interpreted as a (partial) rational explanation of some of these well-known anomalies that are robustly present in the data.

Our findings are related to several strands in the extensive literature on cross-sectional asset pricing, which in itself is too vast to cite in full here. The empirical struggles of the CAPM are well-known. However, while there is consensus that the unconditional performance of the model is unsatisfactory (Roll (1977); Bhandari (1988); Fama and French (1992)), the conditional performance of the model continues to be debated (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001; Lewellen and Nagel, 2006), Gormsen and Jensen (2024)). Moreover, Savor and Wilson (2013, 2014) argue that while the CAPM performs poorly unconditionally, most of the market risk premium is realized around major announcement dates, and the CAPM performs well during these periods. Our results are consistent with this literature that highlights the merits of the CAPM in certain dimensions. We find that one of the two components of the market beta (the negative market beta), is priced, while the other component (the positive market beta) is not. This finding is consistent with the findings in Savor and Wilson (2013, 2014), in the sense that the CAPM is shown to work when using data that have a favorable signal to noise ratio. The valuable signal resides in the negative market beta, while the positive market beta adds noise, thereby invalidating the overall market beta.

Our results are most closely related to the literature that generalizes and decomposes the standard market beta to explain the cross-sectional variation in returns, and specifically the downside beta of Ang et al. (2006b) and the realized semibetas of Bollerslev et al. (2022). Note that the difference between our proposed negative and positive market betas with the approach in Ang et al. (2006b) and the realized semibetas of Bollerslev et al. (2022) is subtle yet radical. To compute betas for a given stock i, Ang et al. (2006b) and Bollerslev et al. (2022) both distinguish between positive and negative realizations of the market return, and Bollerslev et al. (2022) also distinguish between positive and negative returns on stock i. We instead consider the entire cross-section of co-movements between the return on stock i and all other stocks, and then group these in positive and negative co-movements. Note that while this idea is conceptually simple, its implementation is more time-intensive than other approaches due to the large number of permutations. The literature contains many other decompositions of market beta. Despite superficial and semantic resemblance, these approaches are very different. For instance, Campbell and Vuolteenaho (2004) distinguish the separate betas for cash-flow and discount rate news, which they refer to as good and bad beta. Our negative market beta can be interpreted as a hedge and therefore a good beta, but the economic story is entirely different.

As mentioned above, the existing literature on the cross-section of (stock) returns is too vast to cite in full here. However, because our cross-sectional predictor is motivated by theory and economic intuition, it is consistent with recent trends in this literature. The plethora of cross-sectional predictors, anomalies, and resulting factor models has become a distraction to the literature and an impediment to progress. Cochrane (2011) coined the term "factor zoo" to describe this state of affairs. The response has been on the one hand to emphasize parsimony, and on the other hand to encourage factors suggested by theory (Harvey et al., 2015; Harvey, 2017; Lewellen et al., 2010). Our approach is very much in line with this research agenda.

The remainder of the paper proceeds as follows. Section 2 discusses the model and the data used in the empirical analysis. Section 3 presents the predictive cross-sectional results and discusses the properties of the resulting long-short portfolio. Section 4 presents robustness analysis and additional results, and Section 5 concludes.

2 Model and Data

We introduce the decomposition of the market beta into negative and positive market beta. We discuss the economic prior on the sign and magnitude of the price(s) of risk. Then we discuss the data and the descriptive statistics for the negative and positive market beta.

2.1 Decomposing Market Beta

We propose a decomposition of a firm's conventional CAPM market beta based on its negative and positive comovements with all other stocks. The CAPM market beta measures the covariance of a stock's return with respect to market and is given by:

$$\beta_i = \frac{cov(R_i, R_m)}{\sigma_m^2}, \tag{1}$$

where R_i represents the stock excess return of firm i, R_m is the market excess return, and σ_m^2 is the market variance. The market excess return is the weighted average of the firm-specific stock returns, where the weights are proportional to the market capitalization of the firm i.e.,

$$R_m = \sum_{j=1}^{N} w_j R_j, \tag{2}$$

where w_j is the weight of firm j in the market portfolio and N is the total number of firms. Rewriting the definition of the market beta in equation (1) using equation (2), we get

$$\beta_i = \frac{cov\left(R_i, \sum_{j=1}^{N} w_j R_j\right)}{\sigma_m^2} \tag{3}$$

$$= \frac{\sum_{j=1}^{N} cov(R_i, w_j R_j)}{\sigma_m^2}. \tag{4}$$

We use the definition of the market beta in equation 4 to motivate the following decomposition of the market beta into negative and positive betas, as follows:

$$\beta_i = \frac{\sum_{j=1}^{N} 1_{cov(R_i, w_j R_j)<0} cov\left(R_i, w_j R_j\right)}{\sigma_m^2} + \frac{\sum_{j=1}^{N} 1_{cov(R_i, w_j R_j)\geq 0} cov\left(R_i, w_j R_j\right)}{\sigma_m^2}$$
$$= \beta_i^- + \beta_i^+. \tag{5}$$

2.2 Priors on the Price of Risk

The CAPM stipulates that the expected return on any asset i is given by:

$$\begin{aligned} E[R_i] &= \beta_i E[R_m] \\ &= (\beta_i^- + \beta_i^+) E[R_m] \\ &= \beta_i^- E[R_m] + \beta_i^+ E[R_m] \end{aligned} \tag{6}$$

The objective of this paper is to empirically examine and document the ability of the β_i^- and β_i^+ components of total beta to explain and predict the cross-section of stock returns, and to compare the performance of these components with that of β_i. That is, we compare the following specifications of the cross-section of expected returns:

$$E[R_i] = \beta_i E[R_m] \tag{7}$$

$$E[R_i] = \beta_i^+ E[R_m] \tag{8}$$

$$E[R_i] = \beta_i^- E[R_m] \tag{9}$$

We also pursue the following specification:

$$E[R_i] = \beta_i^+ E[R_m] + \beta_i^- E[R_m] \tag{10}$$

and two other bivariate specifications obtained by considering β_i together with either β_i^- or and β_i^+ as characteristics that determine the cross-section of stock returns.[4] At the risk of overcomplicating things, it may be useful to be explicit about the assumptions underlying these different univariate and multivariate specifications. First, the bivariate model in equation (10) seems like the natural one to consider under the maintained assumption of the CAPM and the decomposition in equation (6). However, denoting the prices of risk associated with β, β^-, and β^+ as λ, λ^-, and λ^+ respectively, note that the bivariate models that include β_i and either β_i^- or and β_i^+ are also implied by equation (6) under certain assumptions. In fact, these empirical specifications are all equivalent (and reduce to the CAPM) if the risk premiums satisfy:

$$\lambda = \lambda^- = \lambda^+ = E[R_m] \tag{11}$$

This also implies that the null hypothesis in equation (11), a positive price of risk equal to the excess return on the market, is the most interesting one to use for the empirical analysis of the negative and positive betas. This null hypothesis is also very intuitive. Just as a higher β_i represents higher risk in the CAPM, a higher (less negative) β_i^- represents more comovement with (parts of) the market portfolio, and thus more risk. The same is true for β_i^+.

While theory does not offer any guidance as to the a priori expected importance of the

[4] Note that the model that combines β_i, β_i^-, and β_i^+ is not identified.

β_i^- and β_i^+ components for pricing and predicting the cross-section, our intuition is that a stock's β_i^- may be especially important, because it can be interpreted as a hedge. Indeed, similar to the CAPM intuition that stocks that negatively correlate with the market index are more valuable and therefore more expensive with a smaller expected return, it is the stocks that negatively co-move with the cross-section that are most valuable, and therefore have low expected returns.

As with any cross-sectional application, we have to choose the window over which we compute the exposures. In our baseline implementation, we use a one-month window. That is, at the end of each month, we compute β_i, β_i^-, and β_i^+ using daily excess returns during the calendar month. We also investigate the robustness of our results when using a three-month window.

2.3 Data and Descriptive Statistics

We obtain daily stock return data from the Center for Research in Security Prices. Our sample period is from June 1962 to December 2023. We also obtain data on the market value of equity, defined as the product of stock price and number of shares outstanding. We compute book-to-market as the ratio of the book value of equity and the market value of equity, following Fama and French (1992). We exclude stocks with prices below $5 at the time of portfolio formation, to avoid the effect of outliers due to penny stocks.

We compute betas every month using daily data and study cross-sectional predictability one month ahead. This constitutes the time-intensive part of the exercise, because it involves recursively computing an N by N matrix. In our baseline results, we construct the betas every month using one month of daily data. Our results are robust to the choice of window used for the construction of the betas. In Section 4.2 we also report on three- and six-month windows in addition to the baseline one-month window.

Figure 1 presents the distribution of the total β as well as β_i^- and β_i^+. This is the unconditional distribution which combines all estimates of a given beta across all firms N and times T. The first three columns in Panel A of Table 1 present descriptive statistics for the three betas. The average CAPM β is 0.84, while the average negative component β^- is -0.60 and the average positive component β^+ is 1.47. Panel B presents the average cross-sectional correlations between the three betas. We compute the cross-sectional correlation for each month and average it over time. The cross-sectional correlation between the total β and β^+ is high (85%). The correlation between total β and β^- is lower at 44%, suggesting that β^- captures information that is distinct from that contained in the total β. Moreover, β^- and β^+ display very low correlation.

Figure 2 plots the monthly time series of the 25th, 50th, and 75th percentiles of β, β^-, and β^+ for 1962-2023. Note that because the variation of a given percentile of β^- and β^+ far exceeds that of β, the percentile time series of β^- and β^+ are very highly negatively correlated. NBER recessions are indicated by the shaded regions. There is no discernible relation between the percentile time series of β and NBER recessions in Panel A, and the same remark applies to the percentile time-series of β^- and β^+ in Panels C and D. Panel B plots the annualized monthly realized volatility of the S&P 500, computed using daily returns. The median (and the entire distribution) of β^- and β^+ in Panels C and D fluctuate a lot in two periods, 1963-1967 and 1992-1996. Panel B indicates that these are low-volatility periods.

3 Empirical Results

We first discuss portfolio returns based on univariate portfolio sorts. We then present the results of Fama-MacBeth regressions and inspect the patterns in long-short returns. We document and analyze the relation between the negative market beta and other well-known cross-sectional predictors. Finally, we report the relation with factors based on existing anomalies and well-known factor models.

3.1 Univariate Portfolio Sorts

We first present the results from simple univariate portfolio sorts. At the end of each month, we sort firms into ten portfolios based on a given characteristic and report the portfolio returns for the next month. Panel A of Table 2 reports the time-series average of the value-weighted returns for each of the market β decile portfolios as well as the t-statistic and the average (ex-ante) CAPM market β for each of the portfolios. Consistent with the literature, the results do not support the CAPM. The portfolio returns display a hump-shaped pattern as a function of the CAPM β, with returns initially increasing with β and then decreasing. Based on portfolios 1 and 10, the high-minus-low portfolio generates an average monthly return of minus six basis points, with a t-statistic of 0.26.

Panel B presents our findings for univariate sorts based on β^-, and the results are a stark contrast to the results for the CAPM in Panel A. The returns on the decile portfolios increase monotonically from portfolio 1 to portfolio 5; the pattern is flat for portfolios 6-10. The high-minus-low portfolio based on deciles 1 and 10 generates an economically significant monthly average return of 43 basis points, or 7.44% on an annual basis. This can be compared to the average market risk premium in our sample, which is equal to 5.59% per year. The t-statistic for the average high-minus-low portfolio return is 2.51. Panel B also reports the average (ex-ante) β^-, which of course increases by construction, and the average CAPM β for each portfolio. Note that the CAPM β increases between portfolios 1 and 9. While this might be interpreted as suggesting that β^- does not contain additional information compared to β, this is not the case. We discuss this in more detail below.

For completeness, we also report on univariate sorts based on β^+ in Panel C of Table 2. These results display some similarities with the results based on β in Panel A. For instance, the average portfolio returns also exhibit a strong hump-shape, and total β monotonically increases with β^+. Like the sort on β in Panel A, the β^+ in Panel C does not yield statistically significant results or meaningful conclusions. The high-minus-low portfolio based on portfolios 1 and 10 results in a statistically insignificant negative return. Finally, the last column of Panel C also indicates that β^- does not systematically covary with the β^+ decile portfolios. This finding confirms the low cross-sectional correlation between β^- and β^+ reported in Panel B of Table 1.

In summary, the proposed β^- exposure captures meaningful information and helps explain cross-sectional differences in stock returns. The average long-short portfolio return based on β^- is economically and statistically significant and positive. These results suggest that β^- captures risk better than the exposure than the market beta, the traditional measure of aggregate market risk. An alternative interpretation of these findings is that the cross-sectional performance of total β suffers from the inclusion of β^+, which does not help explain cross-sectional differences and adds noise to β^-.

3.2 Fama-MacBeth Regressions

We report on the results of Fama-MacBeth regressions mainly to demonstrate that the explanatory power of β^- remains in the presence of other characteristics that have been documented in the literature. However, we start our exploration by presenting the results of Fama-MacBeth regressions in the absence of these competing determinants of cross-sectional returns. Specifically, Table 3 presents the results from univariate and multivariate Fama-MacBeth regressions based on β, β^-, and β^+. Consistent with the single sorts in Table 2, the betas are constructed using one month of daily returns. Each month, we run cross-sectional predictive regressions and we report the average estimated coefficient. The table also reports the Newey-West t-statistics based on three lags. These results are useful to verify if the sorting results β^- in Panel B of Table 2 also emerge in a linear setup. Moreover, the multivariate regressions may provide further insights into the relation between β, β^-, and β^+.

The univariate regression of returns on lagged total β in column (1) of Table 3 results in a negative estimate of the risk premium, contrary to theory, but the estimate is not statistically significant. This once again confirms the findings in the existing literature that total β has limited explanatory for the cross-section of stock returns. The estimated coefficient for β^- in column (2) is 71 basis points with a t-statistic of 6.74. This estimate implies a market risk premium of 8.52 percent (12 x 0.71), as compared to the average market risk premium in our sample of 5.59 percent. When we control for total β or β^+ in columns (4) and (5), the estimate of the risk premium does not change much.[5] The t-statistics are smaller compared to column (2), but the estimates are still highly statistically significant.

[5]Note that because of the linear relation between β, β^-, and β^+, we can not control for both.

3.3 The Dynamics of Long-Short Returns

Figure 3 plots the indexes based on monthly value-weighted long-short returns of decile portfolios, sorted on β, β^-, and β^+. Given the estimated signs of the prices of risk, we report on long-short strategies that bet on β^- and bet against β and β^+.[6] The indexes are initialized at 100. Panels D and E provide more detail on the time series for β^- in Panel C. Panel E resets the β^- index at 100 in 1993, which helps with identifying the time-variation prior to 1993 in Panel D.

The plots in Figure 3 reflect the large differences between the (absolute values of the) average long-short returns in Table 2. However, the main purpose of Figure 3 is to highlight the time-variation in the long-short returns, and to identify (extended) periods when these returns were positive and negative. To assist with this, the blue line in Panel A of Figure 4 plots the (non-cumulative) long-short return for β^-. Instead of the (noisy) monthly returns, Figure 4 plots 60-month averages. These figures suggest that the large average long-short β^- return is driven by positive long-short returns during most of the sample period. Betting on β^- results in several periods of negative average returns in our sample, these occurrences are relatively rare. Panel A of Figure 4 indicates that the moving average is negative in 172 out of 679 months (25.33%), and these negative moving average returns occur in four periods. Figure 3 highlights that the period between 1980 and 2000 is associated with especially high long-short returns.

Another interesting aspect of Figure 3 is the co-movement between the three time series of long-short returns (and the corresponding indexes). The first three entries in the top

[6] This implementation is chosen for (visual) convenience. While our prior for all three betas is a positive price of risk, the (insignificant) estimates for β and β^+ are negative. To facilitate the comparison with the time series for β^- in Panel B, we therefore construct the long-short returns in Panels A and C by betting against β and β^+.

panel of Table 6 reports the correlation between the long-short returns based on β, β^-, and β^+. As expected, the long-short returns for β and β^+ are very highly correlated (0.885). The correlation between the long-short return of β^- and β is relatively small (-0.064).[7] We conclude that β^- contains information that is very different from the information in market β, confirming the results from Table 1.

3.4 Controlling for Alternative Cross-Sectional Predictors

We report the results of Fama-MacBeth regressions on β^- and control variables that have been documented to have cross-sectional predictive power in the existing literature. Our main objective is to study if the cross-sectional predictive power of β^- is related to that of these other predictors. Before we turn to the results of these regressions, we first explore the relation with these other characteristics by simply reporting the averages for these variables in the decile portfolios used in Table 2.

Table 4 reports the averages of several well-known cross-sectional predictors for the β, β^-, and β^+ decile portfolios. We report on the size variable of Banz (1981) and Fama and French (1992), the book-to-market variable of Fama and French (1992), momentum (MOM) (Jegadeesh and Titman, 1993), realized variance (RV) (Andersen et al., 2001), idiosyncratic volatility (IVOL) (Ang et al., 2006b), reversal (REV) (Jegadeesh, 1990; Lehmann, 1990), Illiquidity (ILLIQ) (Amihud, 2002), turnover (Kumar, 2009), and volume.

The descriptive statistics for the β^- decile portfolios in Panel B indicate a (near) monotonic relation between β^- and several of these variables, specifically size, momentum (MOM), realized variance (RV) and idiosyncratic volatility (IVOL), reversal (REV), turnover, and illiquidity (ILLIQ). It is striking that none of these momotonic patterns obtain for the β

[7] The correlation between the β^- long-short return and the market risk premium is -0.086.

decile portfolios in Panel A, except for illiquidity. Another striking observation is that the decile portfolios for β^+ in Panel C are also associated with monotonic patterns in MOM, RV, IVOL, REV, turnover, and volume. Perhaps more interestingly, we also observe a monotonic pattern for BTM in Panel C, which we do not obtain in Panels B and C.

We conclude that the decile portfolios for β^-, and β^+ exhibit many monotonic patterns in well-known cross-sectional predictors of returns. In several cases, these patterns do not obtain for the β decile portfolios. The cross-sectional predictive power of several of these stock characteristics are often perceived as anomalies, in the sense that we have no economic intuition for their sign, or economic intuition yields the opposite sign. If the sign for the price of risk associated with β^- is consistent with theory and economic intuition, this may provide a resolution for these important anomalies such as size and volatility.

Table 5 further explores the relation between β^- and these cross-sectional predictors through Fama-MacBeth regressions. The column labeled "Univariate" reports on the results of univariate regressions. Because of their central place in the literature, the regressions in columns (1)-(8) all include the size variable of Banz (1981) and Fama and French (1992) and the book-to-market variable of Fama and French (1992). First consider the performance of β^- in the presence of size and book-to-market in column (1). The estimated risk premium on β^- is very similar to the estimate from the univariate regression, and the statistical significance is also similar. Both size and book-to-market enter with the expected sign, negative and positive respectively, and they are both statistically significant.

Columns (2)-(8) report on Fama-MacBeth regressions that also contain the other controls (one at a time). Most of the controls enter with the expected signs in the univariate regresisons and in columns (2)-(8), but ILLIQ, turnover, and volume are not always significant. The results indicate that the estimated risk premium on β^- is robust and statistically significant, but the cross-sectional relation between β^- and some of the controls, especially the two volatility variables (RV and IVOL), affects the magnitude of the loading on β^- and the associated t-statistic.

3.5 Alternative Factors and Factor Models

We further explore the relation between β^- and the existing literature, this time by studying the relation between the β^- factor based on the long-short return and other factors available in the literature. The top panel of Table 6 reports correlations between the factors based on β, β^-, and β^+. The middle panel reports the correlation between the β^- factor and the market factor, as well as factors estimated from long-short returns based on the characteristics in Table 5. The bottom panel reports the relation with the market factor and the Investment (INV) and Operating Profitability (OP) factors from the Fama-French five-factor model (Fama and French, 2015). Table 6 indicates that the β^- is highly positively correlated with the OP factor, and highly negatively correlated with the size factor (SMB), the illiquidity factor (ILLIQ), and the two volatility-based factors (RV and IVOL).

Figure 4 further explores these co-movements. All panels plot 60-month moving averages. These are less noisy, which makes the relation easier to see. Panels B-D of Figure 4 illustrate the relation between the β^- factor and three highly correlated factors: the ones based on size(Panel B), realized variance (Panel C) and illiquidity (Panel D). Panels E and F plot the relation with the momentum and volume factors respectively. Table 6 indicates that these factors are not highly correlated with the β^- factor, and the plot confirms this.

Panels B-D confirm that the β^- factor is related to size, variance, and illiquidity. Note that in all cases, we plot the factor that is related to the β^- factor. This means that we sometimes plot the inverse of the usual factor. For instance, for the size factor in Panel

B, we plot large minus small because of the negative correlation between the β^- and SMB factors. Similarly, the illiquidity factor in Panel D is based on low minus high illiquidity. For the realized variance, we plot low RV minus high RV. Figure 4 clearly illustrates that the β^- factor is related to size, variance, and illiquidity. Interestingly, the relation seems particularly strong for size and illiquidity. In contrast, in the FM regressions in Table 3, the relation with the RV characteristic seems stronger than the relation with size and illiquidity.

Table 7 reports the intercepts in the time-series regressions of the time series of the long-short β^- return on the factors from several well-known factor models: the Fama-French three-factor model (FF3) (Fama and French, 1993), the FF3 model augmented with the momentum factor (Carhart, 1997), and the Fama-French five-factor model (FF5) (Fama and French, 2015). The resulting intercepts correspond to the alphas associated with the β^- strategy after accounting for these factors. These results confirm that the cross-sectional predictive power of β^- cannot be explained by these factor models.

We conclude that β^- is related to several well-known predictors, especially size, (idiosyncratic) variance, and illiquidity. The relation with size and illiquidity is intriguing. While the cross-sectional predictive power for illiquidity is suggested by economic intuition, this is not the case for size and variance. The correlation of β^- with these cross-sectional predictors may therefore provide an economically based explanation for these anomalies.

4 Robustness Analysis and Additional Results

In this section we present a number of robustness analyses. First we further explore the relation between β^- and β through bivariate portfolio sorts. Then we document the robustness of our results when using alternative estimation windows and we present the results of alternative long-short portfolio strategies and different samples.

4.1 Bivariate Portfolio Sorts

We further explore the relation between β^-, β, and β^+. Panel A of Table 8 presents the results of a double sort, where we first sort the stocks into five portfolios based on total β and then based on β^- within each total β portfolio. The high-minus-low β^- portfolio generates on average positive returns regardless of β, but the returns are not always statistically significant. There is no obvious pattern in the economic magnitude of the high-minus-low β^- return as a function of β. We also perform double sorts for positive beta. We first sort the stocks into five portfolios based on total β and within in each portfolio, we sort based on β^+. Panel B presents the results of this double sort. Consistent with the univariate sorts, higher β^+ is associated with lower returns.

Panel C presents the results of double sorts where we first sort on β^+ and then on β^-. The high-minus-low β^- portfolio again generates on average positive returns except for the bottom β^+ quintile. The high-minus-low β^- return clearly increases with β^+. This is confirmed in Panel D when we first sort on β^- and then on β^+. We conclude that in these double sorts with β, and β^+, higher β^- is very consistently associated with higher returns.

Table 9 further explores the relation between β^- and the other cross-sectional predictors studied in Tables 4 and 5. We focus on the predictors that we found to be most closely related with β^-, namely size, illiquidity, and the two volatility variables (RV and IVOL).

For completeness, Panels A-D present the results of univariate sorts for these four predictors. The results in Panels A-C are consistent with the signs of the univariate regressions in Table 5 and the existing literature. Larger firms and more volatile returns are associated with lower returns. Somewhat surprisingly, illiquidity in Panel D is not statistically significant, but this is consistent with the results in Table 5.

Panels E-H present the results from double sorts. We first sort on the competing characteristic and then on β^-.[8] The most important finding is that high β^- is consistently associated with high returns, except for low-volatility stocks. However, the results for β^- are more economically and statistically significant for small and illiquid stocks, in addition to higher volatility stocks.

4.2 The Beta Estimation Window

Our baseline results in Tables 2 and 3 use estimates of β_i, β_i^-, and β_i^+ that are based on one month of daily data. We now show that our results are robust to the length of this estimation window.

Table 10 reports on single sorts based on β_i^-, β_i, and β_i^+, using three- and six-month windows of daily data to estimate the betas. The results for β_i^- are remarkably robust. Not only are the three estimates all negative and statistically significant, the estimated magnitudes of the long-short portfolios are relatively similar. The estimate is 0.42% in the baseline case (three-month window), compared to 0.62% when using a one-month window and 0.48% when using a six-month window. This corresponds to annualized long-short returns of 5.04%, 7.44%, and 5.76% respectively, while the market risk premium in our sample is 5.59% per year. The patterns in the portfolio returns are also similar. The results for β_i and β_i^+ are consistent with those in Tables 2 and therefore not very interesting. The long-short return estimates are not statistically significant and often have the wrong (negative) sign.

[8]For completeness, Panels A-D of Table A.1 report results while sorting on β^- first and Panels E-H report on unconditional double sorts.

4.3 Other Long-Short Portfolio Strategies

Table A.2 present the results from univariate sorts based on quintiles rather than deciles. The average return on the β_i^- long-short portfolio is 34 basis points, compared to 43 basis points for the decile portfolios in Table 2. The t-statistics on the β_i^- long-short portfolios are also similar. The results for the β_i and β_i^+ long-short portfolios also yield the same conclusions as the results in Table 2.

4.4 Portfolio and Sample Composition

We provide additional insight into the structure and composition of the decile portfolios. First we analyze the dynamics of these portfolios. Table 11 presents the transition matrix of the β_i^- decile portfolios. Rows are portfolio assignments in month t, and columns are portfolios that are transitioned to in month $t+1$. Each row adds up to 100%. The diagonal indicates a fair amount of persistence for the low (P1) and high (P2) portfolio, and significantly less persistence for the P2-P8 portfolios. When the P1 and P10 stocks transition to another portfolio, this is also much more likely to be a portfolio with low respectively high β_i^-. We conclude that the transition matrix supports the cross-sectional predictive power of β_i^-.

Figure 5 illustrates the composition of the decile portfolios and how it changes over time. We plot a heatmap based on the 12 Fama-French industries by year. Table A.3 in the Appendix provides an overview of these 12 industries. For each industry-year, we identify the dominant β^- portfolio based on the highest share of an industry's stocks representation relative to the number of stocks in portfolio, i.e., for each industry-year we pick the portfolio with the maximum ratio of portfolio's stock count in the industry divided by total stocks in the portfolio that year. We then plot this over time, with blue representing the low return portfolios and red the high-return portfolios.

Figure 5 is very insightful. It clearly indicates that there is a distinct relation between the β_i^- portoflio deciles and industry, but it is also evident that this relation changes over time. The industries that are predominantly high β^- (in red) over the entire sample, and therefore associated with higher returns, are indexed by 8, 5, 11, and 3. These industries are utilities, chemicals, finance, and manufacturing. The association with high β^- is especially strong for utilities and chemicals. One industry is reliably very low β^- (in blue) over the entire sample, and therefore associated with lower returns. This is industry 12, which stands for "Other" (Mines, Construction, Building Materials, Transportation, Hotels, Business Services, and Entertainment). Industry 9 (shops) is mostly blue throughout the sample. Industry 6 is reliably blue except towards the end of the sample. This industry is business equipment (computers, software, and electronic equipment). Industry 10 exhibits the opposite pattern: it is reliable blue except at the start of the sample. This industry corresponds to healthcare, medical equipment, and drugs. A final noteworthy stylized fact is that industry 1 (consumer nondurables) clearly switches from blue (low β^-, low return) to red (high return) over the sample period.

We also document the robustness of our results to the sample composition. Table A.4 reports on a sample with a larger cross-section, due to the fact that we include all stocks with prices higher than \$1, rather than using the \$5 cutoff in Table 2. The results are consistent with the baseline results. The long-short portfolios for β_i and β_i^+ are not significant economically or statistically. The average long-short return for β_i^- exceeds the one in Table 2 and the t-statistic increases. Table A.5 reports on a sample that excludes financials. The results are very similar. Sorting on β_i and β_i^+ does not yield economically or statistically significant results. The results for β_i^- are similar to the results in Table 2.

4.5 Downside Beta and Semibetas

We document and analyze the relation between the negative market beta and the upside and downside betas of Ang et al. (2006a) and the semibetas of Bollerslev et al. (2022).

4.5.1 The Models

Because we decompose the market beta, one related concept that comes to mind is the upside and downside beta from Ang et al. (2006a). Bollerslev et al. (2022) further expand this idea and introduce the concept of semibetas. These papers decompose firms' market betas based on the sign of the firm's return and the sign of the market return. While our decomposition is also sign-based, it is conceptually completely different. To see this, introduce the notation $R_{i,t}^{-} = \min(R_{i,t}, 0)$ and $R_{i,t}^{+} = \max(R_{i,t}, 0)$. First consider the semibetas in Bollerslev et al. (2022), which are defined as follows:

$$\begin{aligned} \beta_1^N &= \frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R_{1,t}^{-} R_{m,t}^{-}\right) & \beta_1^P &= \frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R_{1,t}^{+} R_{m,t}^{+}\right) \\ \beta_1^{M+} &= -\frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R_{1,t}^{-} R_{m,t}^{+}\right) & \beta_1^{M-} &= -\frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R_{1,t}^{+} R_{m,t}^{-}\right) \end{aligned} \tag{12}$$

with $\beta_1 = \beta_1^N + \beta_1^P - \beta_1^{M+} - \beta_1^{M-}$. In contrast, our decomposition is given by:

$$\begin{aligned} \beta_1^{-} &= \frac{1}{\sigma_m^2}\left(\sum_{j=1}^{N} \min\Big(\frac{1}{T-1}\sum_{t=1}^{T} R_{1,t}\, w_{j,t-1}\, R_{j,t}, 0\Big)\right) \\ \beta_1^{+} &= \frac{1}{\sigma_m^2}\left(\sum_{j=1}^{N} \max\Big(\frac{1}{T-1}\sum_{t=1}^{T} R_{1,t}\, w_{j,t-1}\, R_{j,t}, 0\Big)\right) \\ \beta_1 &= \beta_1^{-} + \beta_1^{+} \end{aligned} \tag{13}$$

Equations (12) and (13) clearly illustrate the conceptual differences between the negative and positive betas proposed in this paper and the semibetas in Bollerslev et al. (2022). In the case of the semibetas in equation (12), the market beta is effectively decomposed by putting the data at each time t into one of four bins, dependent on the covariance between the excess returns on stock i and the market. For the negative and positive betas in equation (13) on the other hand, the information at any time t itself is allocated to different bins on a stock-by-stock basis when computing β_i^- and β_i^+ for a given stock i.

The difference between these concepts can also be seen by comparing the implications for the decomposed betas under the null hypothesis that the CAPM holds. For β_i^- and β_i^+, the prices of risk are equal, as seen in equation (11). For the semibetas, the model reduces to the CAPM if equation (8) in Bollerslev et al. (2022) holds:

$$\lambda^N = \lambda^P = -\lambda^{M+} = -\lambda^{M-}. \tag{14}$$

That is, two of the prices of risk are equal to the market price of risk, while the two remaining ones have the opposite sign.

4.5.2 Empirical Evidence

Table 12 reports on Fama-MacBeth regressions that include the upside and downside βs from Ang et al. (2006a) and the semibetas of Bollerslev et al. (2022).[9] Panel B of Table A.6 in the Appendix provides additional evidence by reporting descriptive statistics and the results of cross-sectional regressions of β^- on these other betas.

Column (1) of Table 12 indicate that the upside and downside betas are priced in the

[9]Bollerslev et al. (2020) and Bollerslev et al. (2022) also analyze semibetas computed from high-frequency returns. We focus on daily semibetas, which can be directly compared with the betas proposed in this paper.

Fama-MacBeth regressions. However, while the downside beta has the theoreticallly expected positive sign, this is not the case for upside beta. Our finding that downside beta outperforms upside beta is consistent with the existing literature.[10] Columns (2)-(3) of Table 12 indicate that the risk premium on β^- remains positive and statistically significant when including upside and downside beta, but the smaller loading is consistent with the evidence from Column (1) of Table A.6.

Columns (4)-(5) of Table 12 report on the semibetas of Bollerslev et al. (2022). Column 4 indicates that in our sample, three of the four semibetas (β_1^N, β_1^P, and β_1^{M-}) are statistically significant. However, the negative sign on β_1^P is inconsistent with theory. Table A.7 in the Appendix reports on univariate sorts for the semibetas. All four long-short portfolios are negative, which is not entirely consistent with the evidence from the Fama-MacBeth regressions in column (4) of Table 12. However, note that the results for β_1^N and β_1^P are statistically insignificant. We conclude that of the four semibetas, the results for β_1^{M-} are the most robust, statistically significant, and intuitively appealing.

When combining the semibetas with β^- in column (5) of Table 12, we find that, similar to the results with downside and upside beta in column (3), the loading on β^- remains positive and statistically significant, but the estimate of the risk premium is smaller than the univariate one in Table 3. The signs on the semibetas in column (5) are consistent with column (4), but the magnitude and statistical significance of the risk premiums associated with β_1^{M+} and β_1^{M-} are significantly different. This is consistent with the evidence from Table A.6 that β^- is more strongly cross-sectionally related to β_1^{M+} and β_1^{M-} compared to β_1^N and β_1^P.

[10] However, the evidence on the pricing of downside beta in the existing literature is mixed. See for instance Ang et al. (2006a), Atilgan et al. (2019), Levi and Welch (2020), and Bollerslev et al. (2022).

5 Conclusion

The empirical literature on the cross-sectional determinants of stock returns and on anomalous patterns in these returns has been one of the most dynamic research areas in finance over the past few decades. However, it eventually became a victim of its own success, leading to a plethora of cross-sectional predictors and pricing factors, which Cochrane (2011) referred to as the factor zoo. A consensus formed that the predictive power of many of these candidate predictors was due to a lack of statistical power and the profession's skewed incentives, which emphasize and reward positive discoveries (Harvey, 2017).

In light of this, the asset pricing literature, and the literature on cross-sectional asset pricing in particular, have started emphasizing parsimony and the importance of theoretically motivated factors (Lewellen et al., 2010). One strand of this literature revisits the CAPM. While the poor unconditional performance of the CAPM remains undisputed, several studies have emphasized its conditional performance (Lewellen and Nagel, 2006; Gormsen and Jensen, 2025) and its performance in samples with a favorable signal-to-noise ratio (Savor and Wilson, 2013, 2014). Other studies show that decompositions of the CAPM's market beta outperform the overall market beta (Ang et al., 2006a; Bollerslev et al., 2022).

This paper proposes a new empirical framework for cross-sectional asset pricing based on a different decomposition of market beta. The framework also generalizes and nests the CAPM. We decompose the firm's traditional CAPM market beta in two components: a negative market beta, which contains the negative correlations between the return of the firm and other firms, and a positive market beta, which contains the positive correlations. The sum of the positive and negative betas is the total market beta, and we expect all three betas to have a positive price of risk. We find that the negative beta, which is the beta component that provides a hedge against the overall market, carries a statistically significant and economically large risk premium of 7.44% per annum. Like the total market beta, the positive beta is not statistically or economically significant. We show that the information contained in the proposed negative and positive betas is economically and intuitively very different from the upside and downside betas in Ang et al. (2006a) and the semibetas of Bollerslev et al. (2022). The estimated price of risk associated with the negative beta is also robust to including other factors and characteristics used in the cross-sectional literature.

References

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

Andersen, Torben G, Tim Bollerslev, Francis X Diebold, and Heiko Ebens, 2001, The distribution of realized stock return volatility, *Journal of Financial Economics* 61, 43–76.

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006a, Downside risk, *The Review of Financial Studies* 19, 1191–1239.

Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006b, The cross-section of volatility and expected returns, *The Journal of Finance* 61, 259–299.

Atilgan, Yigit, Turan G Bali, K Ozgur Demirtas, and A Doruk Gunaydin, 2019, *Downside beta and equity returns around the world* (SSRN).

Banz, Rolf W, 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Bhandari, Laxmi Chand, 1988, Debt/equity ratio and expected common stock returns: Empirical evidence, *The Journal of Finance* 43, 507–528.

Bollerslev, Tim, Jia Li, Andrew J Patton, and Rogier Quaedvlieg, 2020, Realized semicovariances, *Econometrica* 88, 1515–1551.

Bollerslev, Tim, Andrew J. Patton, and Rogier Quaedvlieg, 2022, Realized semibetas: Disentangling "good" and "bad" downside risks, *Journal of Financial Economics* 144, 227–246.

Bollerslev, Tim, Andrew J. Patton, and Rogier Quaedvlieg, 2024, Granular betas and risk premium functions, *Forthcoming in the Journal of Econometrics* .

Campbell, John Y, and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249–1275.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Christoffersen, Peter, Mathieu Fournier, Kris Jacobs, and Mehdi Karoui, 2021, Option-based estimation of the price of coskewness and cokurtosis risk, *Journal of Financial and Quantitative Analysis* 56, 65–91.

Cochrane, John H., 2011, Presidential address: Discount rates, *The Journal of Finance* 66, 1047–1108.

Dittmar, Robert F, 2002, Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns, *The Journal of Finance* 57, 369–403.

Fama, Eugene F, and Kenneth R French, 1992, The cross-section of expected stock returns, *the Journal of Finance* 47, 427–465.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Gormsen, Niels Joachim, and Christian Skov Jensen, 2024, Conditional risk, *Journal of Financial Economics* 162, 103933.

Gormsen, Niels Joachim, and Christian Skov Jensen, 2025, Higher-Moment Risk, *Forthcoming in the Journal of Finance* .

Harvey, Campbell R., 2017, Presidential address: The scientific outlook in financial economics, *The Journal of Finance* 72, 1399–1440.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2015, â€¦ and the cross-section of expected returns, *The Review of Financial Studies* 29, 5–68.

Harvey, Campbell R, and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *The Journal of Finance* 55, 1263–1295.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional capm and the cross-section of expected returns, *The Journal of Finance* 51, 3–53.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *The Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *The Journal of Finance* 48, 65–91.

Kraus, Alan, and Robert H Litzenberger, 1976, Skewness preference and the valuation of risk assets, *The Journal of Finance* 31, 1085–1100.

Kumar, Alok, 2009, Hard-to-value stocks, behavioral biases, and informed trading, *Journal of Financial and Quantitative Analysis* 44, 1375–1401.

Lehmann, Bruce N, 1990, Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* 105, 1–28.

Lettau, Martin, and Sydney Ludvigson, 2001, Resurrecting the (c)capm: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* 109, 1238–1287.

Levi, Yaron, and Ivo Welch, 2020, Symmetric and asymmetric market betas and downside risk, *The Review of Financial Studies* 33, 2772–2795.

Lewellen, Jonathan, and Stefan Nagel, 2006, The conditional capm does not explain asset-pricing anomalies, *Journal of Financial Economics* 82, 289–314.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.

Roll, Richard, 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.

Savor, Pavel, and Mungo Wilson, 2013, How much do investors care about macroeconomic risk? evidence from scheduled economic announcements, *Journal of Financial and Quantitative Analysis* 48, 343–375.

Savor, Pavel, and Mungo Wilson, 2014, Asset pricing: A tale of two days, *Journal of Financial Economics* 113, 171–201.

Figure 1: Unconditional Distribution of Betas

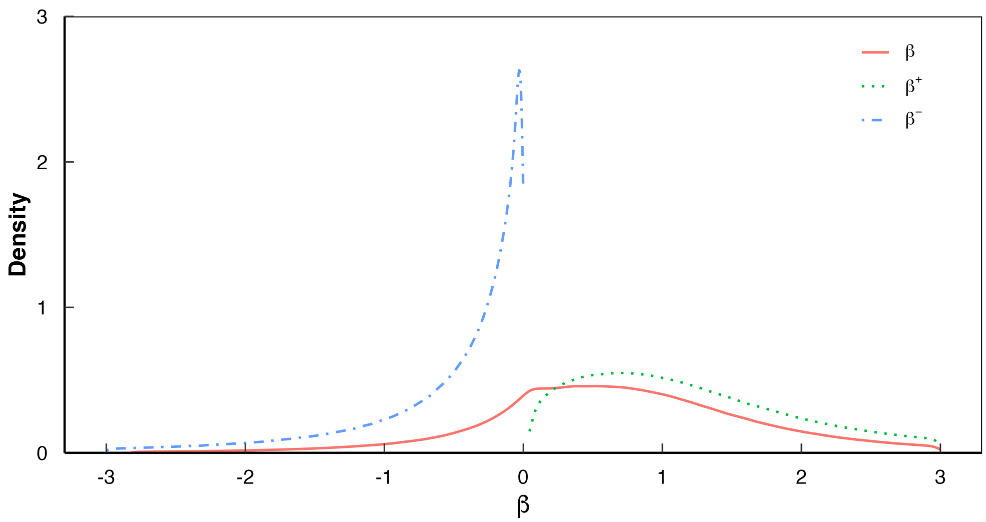
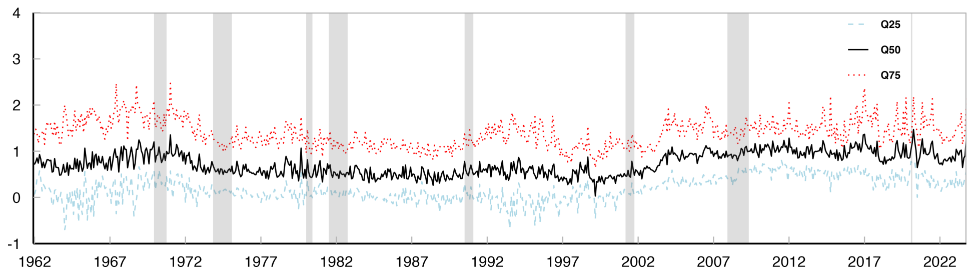
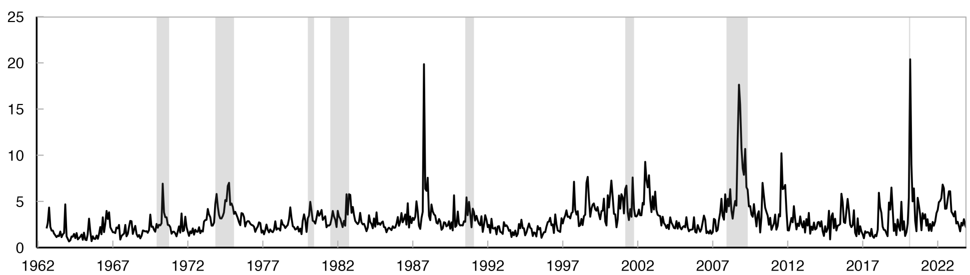


Figure 2: Time-series of Betas. This figure plots the 25th, 50th, and 75th percentiles of β, β^-, and β^+ for each month. The sample covers common and non-penny stocks in the CRSP from 1962 to 2023. Panel B plots annualized monthly realized volatility of S&P 500, computed using daily returns. NBER recession periods are identified in the shaded region.

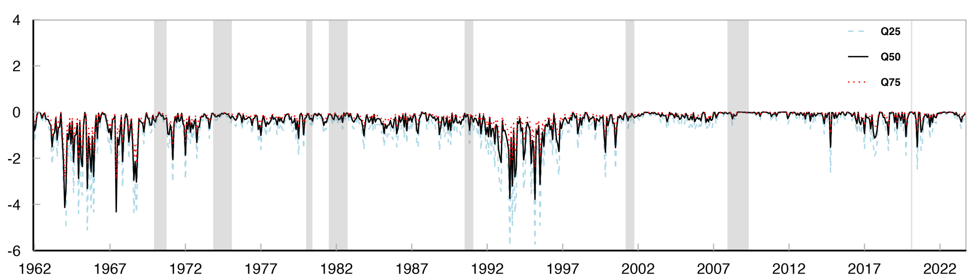
Panel A: β



Panel B: Annualized Market Volatility (%)



Panel C: β^-



Panel D: β^+

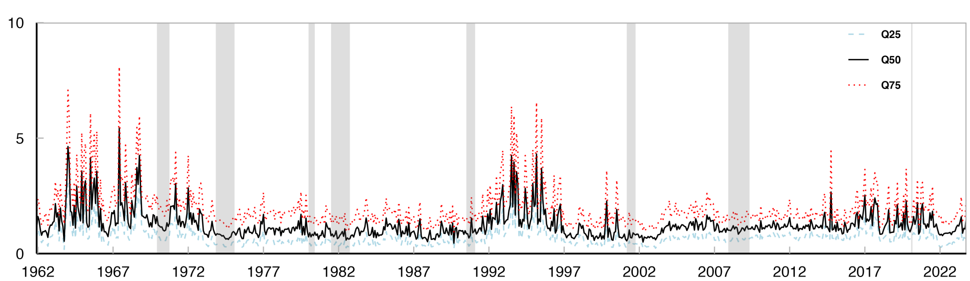
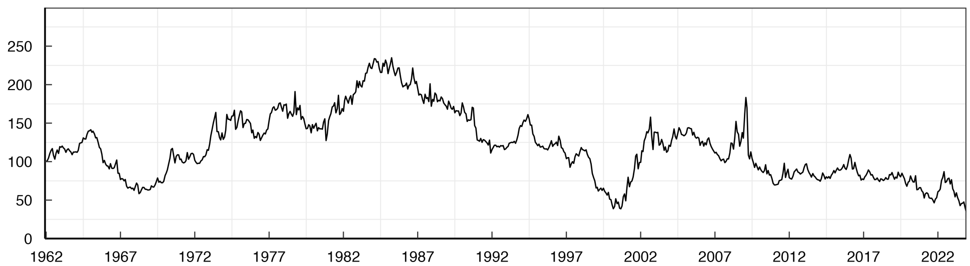
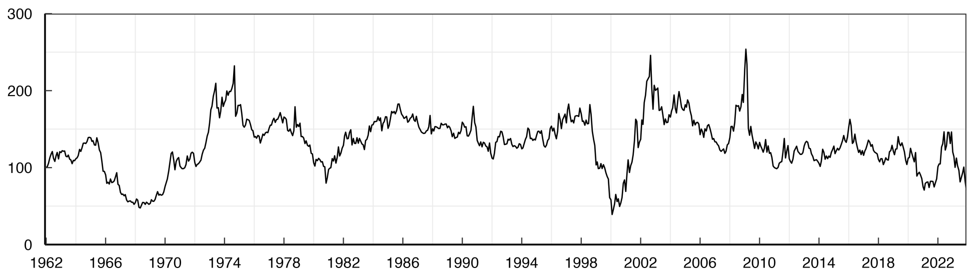


Figure 3: Cumulative Returns of Betas. The figure plots the indexes of monthly long-short strategies on β, β^{+}, and β^{-} sorted value-weighted decile portfolios. The long-short strategies bet on β^{-} and bet against β and β^{+}. Portfolio indexes start at 100.

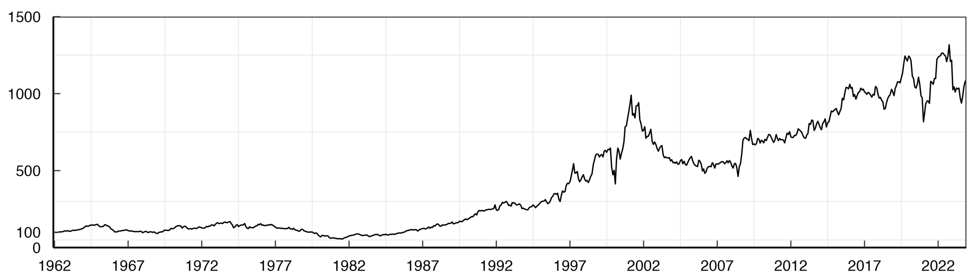
Panel A: β



Panel B: β^{+}



Panel C: β^{-}



Panel D: β^{-} - First half

Panel E: β^{-} - Second half

Figure 4: Moving-Average of Monthly Long-Short Returns The figure plots 60 months moving average of monthly long-short portfolio returns of factors. RV stands for realized variance, the sum of daily squared returns over a month. MOM is momentum, and ILLIQ is Amihud's illiquidity measure.

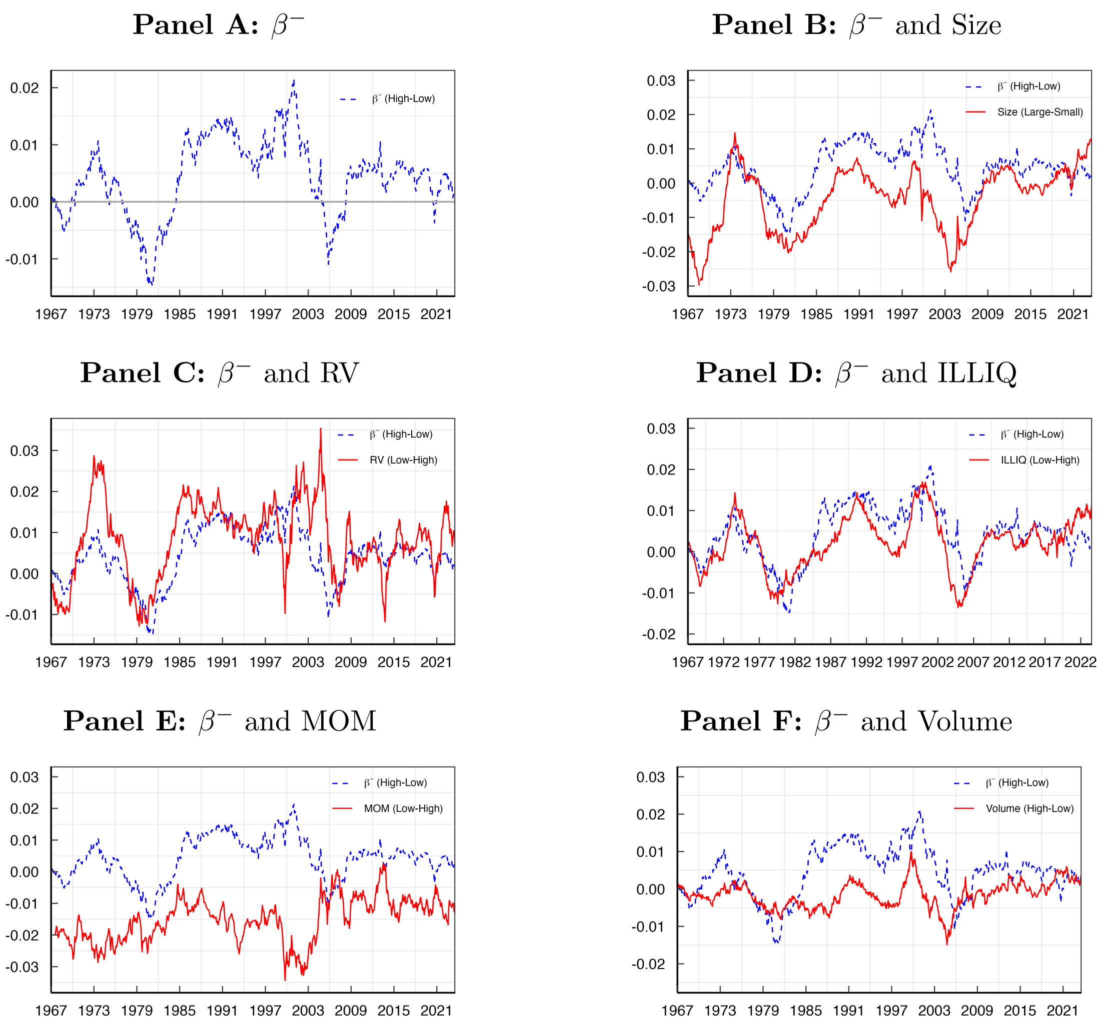


Figure 5: Representation of Industries in β^- Portfolios. We plot a heatmap based on the 12 Fama-French industries by year. We identify the dominant β^- portfolio for each industry-year based on the highest share of an industry's stocks representation relative to the number of stocks in portfolio, i.e., for each industry-year, we pick the portfolio with the maximum ratio of portfolio's stock count in the industry divided by total stocks in the portfolio that year.

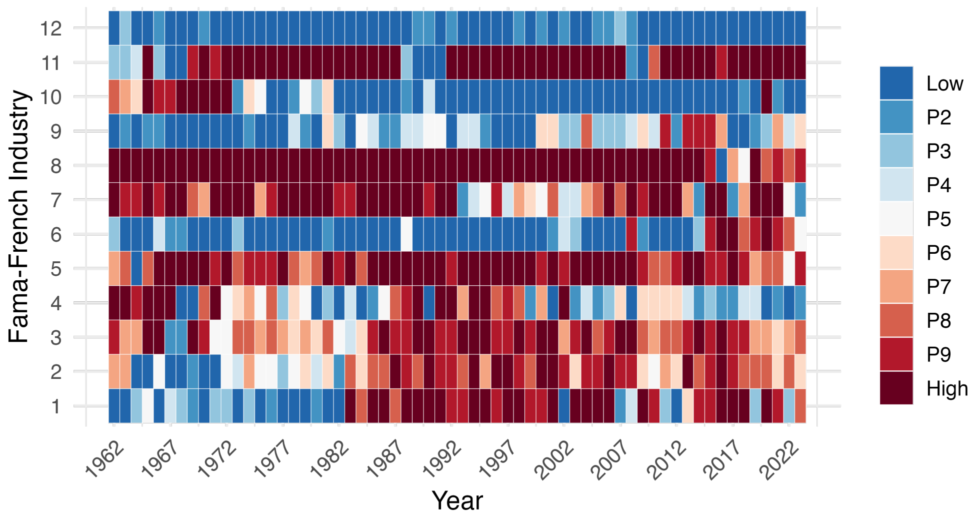


Table 1: Descriptive Statistics. Panel A presents the time-series average of the cross-sectional mean and standard deviation of the monthly beta estimates. Panel B reports average regression coefficients and t-statistics from monthly cross-sectional regressions of β^- on other beta measures. $\bar{R}^2$ is the average R^2 of the monthly cross-sectional regressions. The sample covers common and non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023.

	β	β^-	β^+
Panel A: Cross-Sectional Summary Statistics			
Mean	0.84	-0.60	1.47
Median	0.73	-0.43	1.24
Std	1.11	0.65	1.09
P25	0.20	-0.73	0.73
P75	1.38	-0.26	1.95
Panel B: Cross-Sectional Correlations			
	β	β^-	β^+
β	1	0.44	0.85
β^-		1	-0.05
β^+			1

Table 2: Predictive Single-Sorted Beta Portfolios (Monthly). This table reports predictive single-sorted portfolio returns for the monthly betas estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. For each portfolio, the value-weighted averages for β, β^{+}, and β^{-} are reported. Newey-West robust t-statistics with four lags are presented in parentheses.

Panel A: Stocks sorted by β

Portfolio	Return	t-stat	β	β^{+}	β^{-}
Low	0.78%	(4.23)	−0.69	0.57	−1.29
P2	0.79%	(5.17)	−0.07	0.52	−0.60
P3	0.87%	(5.98)	0.20	0.62	−0.41
P4	0.97%	(6.74)	0.42	0.76	−0.32
P5	0.92%	(6.04)	0.63	0.92	−0.27
P6	0.96%	(5.93)	0.84	1.12	−0.24
P7	0.97%	(5.46)	1.09	1.37	−0.23
P8	1.02%	(5.4)	1.39	1.69	−0.23
P9	0.90%	(4.04)	1.81	2.16	−0.26
High	0.72%	(2.34)	2.70	3.20	−0.37
High - Low	−0.06%	(−0.26)	3.39	2.63	0.92

Panel B: Stocks sorted by β^{-}

Portfolio	Return	t-stat	β^{-}	β	β^{+}
Low	0.51%	(2.15)	−1.78	−0.28	1.48
P2	0.59%	(2.73)	−0.98	0.39	1.38
P3	0.77%	(3.64)	−0.73	0.63	1.39
P4	0.89%	(4.35)	−0.58	0.78	1.39
P5	0.89%	(4.34)	−0.47	0.90	1.41
P6	1.01%	(5.45)	−0.39	0.98	1.41
P7	0.96%	(5.28)	−0.32	1.06	1.42
P8	1.02%	(6.01)	−0.26	1.10	1.41
P9	0.92%	(5.48)	−0.20	1.12	1.37
High	0.94%	(6.16)	−0.12	1.05	1.22
High - Low	0.43%	(2.51)	1.66	1.33	−0.26

Panel C: Stocks sorted by β^{+}

Portfolio	Return	t-stat	β^{+}	β	β^{-}
Low	0.81%	(5.82)	0.30	−0.09	−0.40
P2	0.93%	(6.27)	0.53	0.18	−0.35
P3	0.87%	(6.12)	0.74	0.40	−0.32
P4	0.93%	(6.06)	0.93	0.61	−0.29
P5	0.95%	(6.00)	1.14	0.81	−0.29
P6	1.05%	(6.38)	1.36	1.02	−0.29
P7	0.91%	(4.92)	1.62	1.25	−0.31
P8	0.99%	(4.67)	1.95	1.54	−0.34
P9	0.94%	(4.06)	2.43	1.93	−0.40
High	0.60%	(1.87)	3.51	2.78	−0.59
High - Low	−0.22%	(−0.83)	3.21	2.87	−0.19

Table 3: Monthly Fama-MacBeth Regressions on Betas (Monthly). This table reports monthly Fama-MacBeth cross-sectional predictive regressions of stock returns on the monthly betas estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are presented in parentheses. $\bar{N}$ is the average number of stocks per month and $\bar{R}^2$ is the average R^2 of the monthly cross-sectional predictive regressions.

	Return$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.01008***	0.01246***	0.01253***	0.01436***	0.01438***	0.01427***
	(5.44)	(6.16)	(7.53)	(9.02)	(9.01)	(8.97)
β_{t-1}	-0.0001				-0.00153*	0.00654***
	(-0.16)				(-1.88)	(6.35)
β^-_{t-1}		0.00715***		0.00652***	0.00796***	
		(6.74)		(6.32)	(5.11)	
β^+_{t-1}			-0.00146*	-0.00143*		-0.00766***
			(-1.90)	(-1.83)		(-5.09)
$\bar{N}$	3831.31	3831.31	3831.31	3831.31	3831.31	3831.31
$\bar{R}^2$	0.02	0.01	0.02	0.03	0.03	0.03

Table 4: Summary for Characteristics of Beta Portfolios. This table reports average characteristic of predictive single-sorted monthly beta portfolios, where the monthly betas are estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. BTM, $Turnover$, and $Volume$ are the natural logarithm of the average. $ILLIQ$ is multiplied by 10^6. $Size$ is in millions (\$).

Panel A: Stocks sorted by β

Portfolio	Size	BTM	MOM	RV	IVOL	REV	ILLIQ	Turnover	Volume
Low	19,305	−0.44	0.19	0.02	0.02	0.03	0.64	4.76	17.52
P2	32,979	−0.36	0.15	0.01	0.01	0.01	0.22	4.30	17.65
P3	41,349	−0.35	0.15	0.01	0.01	0.01	0.14	4.23	17.86
P4	45,411	−0.34	0.14	0.01	0.01	0.01	0.11	4.22	17.90
P5	48,300	−0.35	0.15	0.01	0.01	0.01	0.07	4.28	17.99
P6	50,119	−0.40	0.15	0.01	0.01	0.01	0.06	4.33	18.02
P7	63,995	−0.45	0.17	0.01	0.01	0.01	0.05	4.42	18.23
P8	63,658	−0.49	0.19	0.01	0.01	0.01	0.04	4.55	18.30
P9	49,281	−0.51	0.23	0.01	0.02	0.02	0.05	4.77	18.39
High	34,288	−0.51	0.34	0.03	0.02	0.03	0.10	5.26	18.57

Panel B: Stocks sorted by β^-

Portfolio	Size	BTM	MOM	RV	IVOL	REV	ILLIQ	Turnover	Volume
Low	13,197	−0.58	0.27	0.05	0.04	0.06	0.98	5.37	17.79
P2	20,167	−0.53	0.23	0.02	0.03	0.03	0.43	5.07	17.93
P3	28,124	−0.43	0.20	0.02	0.02	0.02	0.3	4.95	18.18
P4	31,518	−0.43	0.20	0.02	0.02	0.02	0.19	4.84	18.10
P5	37,579	−0.42	0.20	0.01	0.02	0.02	0.15	4.74	18.15
P6	45,397	−0.41	0.19	0.01	0.02	0.02	0.10	4.64	18.17
P7	48,602	−0.43	0.18	0.01	0.01	0.01	0.07	4.54	18.24
P8	56,513	−0.44	0.18	0.01	0.01	0.01	0.04	4.43	18.16
P9	62,338	−0.46	0.17	0.01	0.01	0.01	0.03	4.27	18.17
High	71,758	−0.49	0.16	0.01	0.01	0.01	0.01	4.06	18.10

Panel C: Stocks sorted by β^+

Portfolio	Size	BTM	MOM	RV	IVOL	REV	ILLIQ	Turnover	Volume
Low	26,546	−0.34	0.15	0.01	0.01	0.01	0.28	4.13	17.41
P2	39,569	−0.34	0.14	0.01	0.01	0.01	0.16	4.14	17.76
P3	49,101	−0.38	0.14	0.01	0.01	0.01	0.12	4.18	17.91
P4	48,868	−0.37	0.15	0.01	0.01	0.01	0.10	4.24	17.94
P5	48,987	−0.40	0.15	0.01	0.01	0.01	0.07	4.31	17.98
P6	56,528	−0.45	0.17	0.01	0.01	0.02	0.07	4.40	18.13
P7	62,210	−0.49	0.18	0.01	0.01	0.02	0.06	4.51	18.28
P8	51,889	−0.51	0.21	0.01	0.02	0.02	0.06	4.67	18.25
P9	46,212	−0.53	0.27	0.02	0.02	0.02	0.08	4.91	18.41
High	31,328	−0.54	0.38	0.04	0.03	0.04	0.18	5.40	18.58

Table 5: Monthly Fama-MacBeth Regressions on Other Controls (Monthly). This table reports monthly Fama-MacBeth cross-sectional predictive regressions of stock returns on the monthly betas and other controls. The controls include size (Size), book-to-market (btm), realized variance (RV), Amihud's illiquidity (ILLIQ), momentum (MOM), reversal (REV), turnover, and volume. The monthly betas, realized variance, idiosyncratic volatility, illiquidity, turnover, and volume are computed using 1-month window. The sample covers common and non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are presented in parentheses. $\bar{N}$ is the average number of stocks per month and $\bar{R}^2$ is the average R^2 of the monthly cross-sectional predictive regressions.

	Return$_t$								
	Univariate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant		0.03019***	0.02469***	0.03072***	0.0371***	0.02936***	0.03362***	0.02845***	0.03087***
		(4.45)	(3.84)	(4.74)	(6.15)	(4.29)	(4.7)	(4.64)	(4.38)
β^-_{t-1}	0.00715***	0.00621***	0.00579***	0.00354***	0.00332**	0.00439***	0.00589***	0.00613***	0.00634***
	(6.74)	(5.92)	(5.6)	(2.75)	(2.17)	(4.04)	(6.51)	(5.96)	(6.13)
$\log(\text{Size})_{t-1}$	-0.00055*	-0.00095***	-0.00086***	-0.00099***	-0.00131***	-0.00083**	-0.00093***	-0.00101***	-0.00146**
	(-1.90)	(-2.8)	(-2.63)	(-3.04)	(-4.34)	(-2.43)	(-2.73)	(-2.86)	(-2.45)
$\log(\text{btm})_{t-1}$	0.00144***	0.00138***	0.0014***	0.00123***	0.00102**	0.00144***	0.00133***	0.00141***	0.00143***
	(3.32)	(3.15)	(3.45)	(2.92)	(2.54)	(3.26)	(3.04)	(3.52)	(3.63)
MOM_t	0.00794***		0.00708***						
	(5.88)		(5.50)						
RV_{t-1}	-0.082***			-0.087***					
	(-3.02)			(-3.25)					
IVOL_{t-1}	-0.181***				-0.216***				
	(-3.88)				(-4.32)				
REV_t	-0.0280***					-0.0298***			
	(-7.77)					(-8.29)			
ILLIQ_{t-1}	72.1						-220.05**		
	(0.55)						(-2.33)		
$\log(\text{Turnover})_{t-1}$	0.00033							0.00051	
	(0.62)							(1.05)	
$\log(\text{Volume})_{t-1}$	-0.00029								0.00059
	(-1.22)								(1.37)
$\bar{N}$		2826.56	2826.56	2826.56	2826.56	2826.56	2826.56	2826.56	2826.56
$\bar{R}^2$		0.02	0.04	0.03	0.03	0.03	0.02	0.04	0.04

Table 6: Factor Corrrelation Matrix Factors are constructed as monthly long-short portfolio returns. Portfolios bet against β and β^+. $R_m - R_f$, SMB, HML, INV, and OP are obtained from Kenneth R. French's data library. Statistically significant factor correlations at 5% level are presented in bold.

	β	β^-	β^+
β	1	-0.064	**0.885**
β^-		1	**0.279**
β^+			1

	β^-	$R_m - R_f$	SMB	HML	MOM	RV	IVOL	REV	ILLIQ	Turnover	Volume
β^-	1	**-0.187**	**-0.599**	**0.209**	**-0.086**	**-0.556**	**-0.649**	-0.026	**-0.273**	**-0.405**	**-0.142**
$R_m - R_f$		1	**0.296**	**-0.202**	**-0.125**	**0.592**	**0.506**	**-0.268**	**-0.275**	**0.553**	**0.439**
SMB			1	**-0.160**	0.019	**0.587**	**0.689**	**-0.120**	**0.399**	**0.491**	**0.101**
HML				1	**-0.231**	**-0.396**	**-0.377**	0.006	**0.298**	**-0.515**	**-0.406**
MOM					1	-0.028	-0.056	**0.292**	**-0.158**	**0.101**	0.066
RV						1	**0.941**	**-0.139**	**0.084**	**0.813**	**0.463**
IVOL							1	**-0.122**	0.001	**0.777**	**0.394**
REV								1	-0.042	**-0.103**	-0.038
ILLIQ									1	**-0.248**	**-0.491**
Turnover										1	**0.532**
Volume											1

	β^-	$R_m - R_f$	INV	OP
β^-	1	**-0.187**	-0.046	**0.464**
$R_m - R_f$		1	**0.270**	**-0.359**
INV			1	-0.045
OP				1

Table 7: Time-series Regression of Factors This table presents time-series regressions of monthly long-short portfolio returns of β^- on CAPM, Fama-French 3-factor (FF3), Fama-French 3-factor plus Carhart's momentum factor (FF3+MOM), anf Fama-French 5-factor. Fama-French factor portfolio returns are obtained from Kenneth R. French's data library. $\hat{\alpha}$ is the intercept estimate of corresponding time-series regression. Newey-West robust t-statistics are presented in parentheses.

	Dep. Var = β^-			
	CAPM	FF3	FF3+MOM	FF5
$\hat{\alpha}$	0.53***	0.51***	0.58***	0.41**
	(3.26)	(3.80)	(3.75)	(2.89)

Table 8: Predictive Double-Sorted Beta Portfolios. This table reports predictive double-sorted portfolio returns for the monthly betas estimated using 1-month window. For high-low portfolios, Newey-West robust t-statistics with four lags are presented in parentheses.

Panel A: β then β^-

Portfolio	Low β^-	P2	P3	P4	High β^-	High-Low
Low β	0.31%	0.79%	0.87%	0.88%	0.83%	0.51%
						(2.59)
P2	0.75%	1.05%	0.95%	0.94%	0.92%	0.17%
						(1.11)
P3	0.84%	1.05%	1.01%	0.98%	0.90%	0.06%
						(0.33)
P4	0.67%	1.01%	1.02%	1.04%	0.99%	0.33%
						(1.73)
High β	0.17%	0.66%	0.88%	0.93%	0.88%	0.71%
						(3.28)
High - Low	−0.14%	−0.13%	0.01%	0.05%	0.05%	
	(−0.55)	(−0.54)	(0.05)	(0.26)	(0.29)	

Panel B: β then β^+

Portfolio	Low β^+	P2	P3	P4	High β^+	High-Low
Low β	0.83%	0.80%	0.88%	0.71%	0.48%	−0.35%
						(−1.93)
P2	0.98%	0.91%	0.91%	0.92%	0.92%	−0.06%
						(−0.41)
P3	0.97%	0.94%	0.89%	0.99%	0.84%	−0.13%
						(−0.82)
P4	1.04%	1.03%	0.86%	1.07%	0.80%	−0.24%
						(−1.37)
High β	0.94%	0.93%	0.80%	0.69%	0.46%	−0.48%
						(−2.15)
High - Low	0.11%	0.13%	−0.08%	−0.02%	−0.02%	
	(0.66)	(0.74)	(−0.37)	(−0.06)	(−0.06)	

Panel C: β^+ then β^-

Portfolio	Low β^-	P2	P3	P4	High β^-	High-Low
Low β^+	0.86%	0.92%	0.83%	0.92%	0.95%	0.0%
						(0.61)
P2	0.73%	0.99%	0.96%	0.87%	0.90%	0.17%
						(1.08)
P3	0.82%	0.96%	1.05%	1.04%	0.94%	0.12%
						(0.70)
P4	0.58%	0.93%	1.01%	1.03%	0.92%	0.34%
						(2.01)
High β^+	−0.11%	0.53%	0.81%	0.84%	0.92%	1.03%
						(4.94)
High - Low	−0.97%	−0.39%	−0.02%	−0.08%	−0.03%	
	(−3.42)	(−1.45)	(−0.08)	(−0.38)	(−0.14)	

Panel D: β^- then β^+

Portfolio	Low β^+	P2	P3	P4	High β^+	High-Low
Low β^-	0.97%	0.68%	0.66%	0.40%	−0.15%	−1.13%
						(−4.31)
P2	0.77%	0.94%	1.04%	0.88%	0.45%	−0.31%
						(−1.15)
P3	0.93%	0.97%	1.08%	0.98%	0.87%	−0.07%
						(−0.26)
P4	0.93%	0.97%	1.10%	1.06%	1.03%	0.10%
						(0.47)
High β^-	0.99%	0.85%	0.95%	0.95%	0.88%	−0.11%
						(−0.65)
High - Low	0.02%	0.18%	0.29%	0.55%	1.04%	
	(0.14)	(1.12)	(1.67)	(2.86)	(4.60)	

Table 9: Predictive Single- and Double-Sorted Beta Portfolios on Size, Volatility, Idiosyncratic Volatility, and Illiquidity. This table reports predictive double-sorted portfolio returns for the monthly betas estimated using 1-month window. For high-low portfolios, Newey-West robust t-statistics with four lags are presented in parentheses.

Panel A: Stocks sorted by Size

Portfolio	Return	t-stat	β^-	β	β^+
Low	1.27%	(4.73)	−0.39	0.70	1.11
P2	1.25%	(4.94)	−0.30	0.83	1.15
P3	1.14%	(4.81)	−0.25	0.90	1.17
P4	1.15%	(4.91)	−0.21	0.98	1.21
P5	1.14%	(5.07)	−0.19	0.99	1.20
P6	1.10%	(5.27)	−0.16	0.98	1.17
P7	1.02%	(4.95)	−0.14	0.98	1.14
P8	1.05%	(5.47)	−0.12	0.97	1.11
P9	1.00%	(5.46)	−0.1	0.97	1.09
High	0.87%	(5.44)	−0.07	1.03	1.13
High - Low	−0.39%	(−1.95)	0.32	0.33	0.02

Panel B: Stocks sorted by RV

Portfolio	Return	t-stat	β^-	β	β^+
Low	0.87%	(6.75)	−0.16	0.46	0.64
P2	0.94%	(6.56)	−0.21	0.72	0.97
P3	0.98%	(6.12)	−0.26	0.92	1.22
P4	0.92%	(5.5)	−0.31	1.06	1.41
P5	1.00%	(5.23)	−0.36	1.19	1.60
P6	0.99%	(4.69)	−0.43	1.31	1.80
P7	1.08%	(4.78)	−0.51	1.43	2.01
P8	0.80%	(3.01)	−0.61	1.59	2.28
P9	0.63%	(2.07)	−0.79	1.73	2.60
High	0.05%	(0.15)	−1.33	1.89	3.31
High - Low	−0.82%	(−2.71)	−1.17	1.44	2.67

Panel C: Stocks sorted by IVOL

Portfolio	Return	t-stat	β^-	β	β^+
Low	0.91%	(6.57)	−0.15	0.77	0.96
P2	0.95%	(6.29)	−0.22	0.90	1.16
P3	0.94%	(5.84)	−0.27	0.97	1.29
P4	0.97%	(5.42)	−0.33	1.04	1.42
P5	0.98%	(5.05)	−0.39	1.12	1.56
P6	1.04%	(4.62)	−0.46	1.18	1.70
P7	0.98%	(4.05)	−0.55	1.27	1.88
P8	0.68%	(2.59)	−0.67	1.34	2.07
P9	0.63%	(2.07)	−0.85	1.41	2.33
High	0.05%	(0.17)	−1.41	1.48	2.95
High - Low	−0.86%	(−3.17)	−1.26	0.70	1.99

Panel D: Stocks sorted by ILLIQ

Portfolio	Return	t-stat	β^-	β	β^+
Low	0.88%	(5.44)	−0.24	1.06	1.35
P2	0.92%	(4.94)	−0.34	1.00	1.38
P3	0.92%	(4.77)	−0.39	0.96	1.40
P4	0.98%	(4.96)	−0.44	0.93	1.41
P5	0.95%	(4.60)	−0.48	0.88	1.40
P6	0.93%	(4.38)	−0.52	0.85	1.41
P7	0.89%	(4.18)	−0.56	0.80	1.40
P8	0.88%	(4.19)	−0.62	0.72	1.37
P9	0.84%	(4.11)	−0.71	0.59	1.32
High	0.62%	(3.14)	−0.92	0.40	1.34
High - Low	−0.26%	(−1.80)	−0.67	−0.65	−0.01

Panel E: Size then β^-

Portfolio	Low β^-	P2	P3	P4	High β^-	High-Low
Low Size	0.74%	1.11%	1.43%	1.48%	1.51%	0.77%
						(3.97)
P2	0.78%	1.00%	1.25%	1.32%	1.33%	0.55%
						(4.03)
P3	0.81%	1.00%	1.14%	1.29%	1.31%	0.50%
						(4.56)
P4	0.76%	0.95%	1.14%	1.22%	1.10%	0.34%
						(3.37)
High Size	0.81%	0.92%	0.93%	0.93%	0.90%	0.09%
						(0.80)
High - Low	0.07%	−0.19%	−0.50%	−0.56%	−0.61%	
	(0.30)	(−0.97)	(−2.29)	(−3.01)	(−3.61)	

Panel F: RV then β^-

Portfolio	Low β^-	P2	P3	P4	High β^-	High-Low
Low RV	0.92%	0.98%	0.87%	0.92%	0.91%	−0.01%
						(−0.15)
P2	0.87%	1.06%	0.92%	1.02%	0.93%	0.06%
						(0.49)
P3	0.86%	1.01%	1.01%	1.04%	0.98%	0.12%
						(0.77)
P4	0.94%	1.02%	1.00%	0.88%	0.93%	−0.01%
						(−0.05)
High RV	−0.04%	0.23%	0.28%	0.40%	0.70%	0.73%
						(3.18)
High - Low	−0.96%	−0.75%	−0.59%	−0.52%	−0.21%	
	(−3.76)	(−2.89)	(−2.18)	(−1.78)	(−0.76)	

Panel G: IVOL then β^-

Portfolio	Low β^-	P2	P3	P4	High β^-	High-Low
Low IVOL	0.85%	0.94%	0.95%	0.96%	0.94%	0.09%
						(0.92)
P2	0.92%	0.95%	0.91%	1.09%	0.88%	−0.04%
						(−0.33)
P3	0.82%	0.96%	0.99%	1.07%	1.05%	0.24%
						(1.53)
P4	0.81%	0.88%	0.85%	0.85%	0.84%	0.03%
						(0.18)
High IVOL	−0.01%	0.19%	0.26%	0.45%	0.67%	0.69%
						(2.81)
High - Low	−0.87%	−0.75%	−0.69%	−0.50%	−0.27%	
	(−3.41)	(−3.15)	(−2.68)	(−2.09)	(−0.95)	

Panel H: ILLIQ then β^-

Portfolio	Low β^-	P2	P3	P4	High β^-	High-Low
Low ILLIQ	0.75%	0.96%	0.91%	0.94%	0.89%	0.14%
						(1.16)
P2	0.66%	0.90%	1.00%	1.03%	1.01%	0.35%
						(2.38)
P3	0.62%	0.79%	0.98%	1.16%	1.07%	0.45%
						(2.93)
P4	0.47%	0.89%	0.92%	1.01%	1.06%	0.60%
						(3.66)
High ILLIQ	0.26%	0.82%	0.69%	0.95%	1.02%	0.76%
						(4.65)
High - Low	−0.49%	−0.14%	−0.23%	0.01%	0.13%	
	(−2.66)	(−0.88)	(−1.52)	(0.06)	(0.99)	

Table 10: Predictive Single-Sorted Beta Portfolios. Alternative Beta Windows. This table reports predictive single-sorted monthly portfolio returns for the monthly betas estimated using 3- and 6-month windows. The sample covers common and non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. For each portfolio, the value-weighted averages for β, β^+, and β^- are reported.

Panel A: Stocks sorted by β^-

3-month window						6-month window					
Portfolio	Return	t-stat	β^-	β	β^+	Portfolio	Return	t-stat	β^-	β	β^+
Low	0.34%	(1.46)	−0.74	0.11	0.85	Low	0.50%	(2.07)	−0.47	0.28	0.74
P2	0.72%	(3.27)	−0.37	0.53	0.91	P2	0.83%	(3.72)	−0.21	0.62	0.84
P3	0.87%	(3.88)	−0.27	0.71	1.00	P3	0.76%	(3.34)	−0.15	0.76	0.92
P4	0.89%	(4.41)	−0.21	0.82	1.05	P4	0.84%	(3.97)	−0.11	0.87	1.00
P5	1.03%	(5.08)	−0.17	0.91	1.09	P5	0.84%	(4.03)	−0.09	0.94	1.04
P6	0.94%	(4.75)	−0.14	0.95	1.11	P6	0.89%	(4.66)	−0.07	0.97	1.07
P7	0.94%	(5.15)	−0.11	1.00	1.13	P7	0.84%	(4.62)	−0.05	1.01	1.09
P8	0.90%	(5.11)	−0.09	1.04	1.15	P8	0.92%	(5.17)	−0.04	1.03	1.11
P9	0.96%	(5.72)	−0.06	1.06	1.15	P9	0.93%	(5.53)	−0.03	1.04	1.10
High	0.96%	(6.21)	−0.04	1.04	1.10	High	0.98%	(6.32)	−0.02	1.01	1.06
High - Low	0.62%	(3.52)	0.70	0.92	0.25	High - Low	0.48%	(2.65)	0.46	0.73	0.32

Panel B: Stocks sorted by β

3-month window						6-month window					
Portfolio	Return	t-stat	β	β^+	β^-	Portfolio	Return	t-stat	β	β^+	β^-
Low	0.73%	(4.08)	−0.21	0.31	−0.52	Low	0.70%	(3.97)	−0.07	0.26	−0.33
P2	0.89%	(5.96)	0.16	0.38	−0.21	P2	0.94%	(6.96)	0.24	0.36	−0.11
P3	0.89%	(6.10)	0.36	0.51	−0.14	P3	0.85%	(6.22)	0.41	0.50	−0.07
P4	0.91%	(6.09)	0.53	0.65	−0.11	P4	0.88%	(5.88)	0.56	0.63	−0.05
P5	0.98%	(6.36)	0.69	0.79	−0.09	P5	0.96%	(6.19)	0.71	0.77	−0.04
P6	0.90%	(5.5)	0.85	0.95	−0.08	P6	0.88%	(5.26)	0.86	0.92	−0.04
P7	1.00%	(5.7)	1.04	1.14	−0.07	P7	0.96%	(5.33)	1.03	1.09	−0.03
P8	0.89%	(4.65)	1.27	1.37	−0.07	P8	0.94%	(4.66)	1.23	1.30	−0.03
P9	0.89%	(3.78)	1.58	1.70	−0.08	P9	0.90%	(3.79)	1.51	1.59	−0.04
High	0.82%	(2.65)	2.21	2.36	−0.11	High	0.80%	(2.55)	2.06	2.17	−0.05
High - Low	0.09%	(0.36)	2.42	2.05	0.42	High - Low	0.10%	(0.39)	2.13	1.92	0.27

Panel C: Stocks sorted by β^+

3-month window						6-month window					
Portfolio	Return	t-stat	β^+	β	β^-	Portfolio	Return	t-stat	β^+	β	β^-
Low	0.93%	(6.55)	0.24	0.03	−0.21	Low	0.90%	(6.30)	0.22	0.07	−0.14
P2	0.82%	(5.97)	0.42	0.27	−0.15	P2	0.89%	(6.61)	0.39	0.30	−0.09
P3	0.92%	(6.28)	0.58	0.46	−0.11	P3	0.89%	(6.37)	0.54	0.47	−0.06
P4	0.92%	(6.12)	0.73	0.62	−0.10	P4	0.87%	(5.79)	0.68	0.62	−0.05
P5	0.95%	(5.98)	0.88	0.78	−0.09	P5	0.96%	(6.26)	0.82	0.76	−0.04
P6	0.91%	(5.35)	1.05	0.94	−0.08	P6	0.88%	(5.19)	0.97	0.91	−0.04
P7	1.03%	(5.60)	1.23	1.12	−0.08	P7	0.98%	(5.22)	1.14	1.08	−0.04
P8	0.86%	(4.37)	1.46	1.34	−0.09	P8	0.93%	(4.59)	1.35	1.27	−0.04
P9	0.88%	(3.60)	1.79	1.65	−0.10	P9	0.88%	(3.59)	1.64	1.55	−0.04
High	0.77%	(2.47)	2.47	2.26	−0.15	High	0.82%	(2.54)	2.23	2.09	−0.07
High - Low	−0.16%	(−0.58)	2.23	2.23	0.06	High - Low	−0.08%	(−0.29)	2.01	2.01	0.08

Table 11: Transition Matrix. This table presents the transition matrix of β^{-} decile portfolios. Rows are portfolio assignments in month t, and columns are portfolios that are transitioned to in month $t+1$. Each row adds up to 100%.

t/t+1	Low	P2	P3	P4	P5	P6	P7	P8	P9	High	Not in sample
Low	27.11	17.99	13.64	10.70	8.63	6.68	5.02	3.73	2.59	1.95	1.97
P2	17.62	15.84	13.95	12.24	10.49	8.87	7.30	5.64	4.12	2.79	1.15
P3	13.47	13.72	13.24	12.24	11.32	10.02	8.70	7.12	5.47	3.72	0.97
P4	10.53	12.07	12.18	12.10	11.43	10.87	9.88	8.56	6.84	4.71	0.83
P5	8.46	10.33	11.21	11.53	11.47	11.30	10.86	9.82	8.35	5.94	0.74
P6	6.62	8.68	9.82	10.71	11.38	11.61	11.65	11.31	9.96	7.56	0.68
P7	5.16	7.13	8.62	9.61	10.74	11.55	12.26	12.50	12.05	9.73	0.65
P8	3.83	5.67	7.06	8.35	9.70	11.08	12.45	13.57	14.54	13.09	0.67
P9	2.71	4.18	5.47	6.76	8.18	9.90	11.71	14.39	17.29	18.73	0.69
High	1.89	2.93	3.70	4.80	5.89	7.46	9.57	12.86	18.32	31.26	1.34

Table 12: Monthly Fama-MacBeth Regressions on Other Betas, 1-month. This table reports monthly Fama-MacBeth cross-sectional predictive regressions of stock returns on the monthly betas, i.e., β^{Up} and β^{Down}, of Ang, Li, and Xing (2006), and the monthly semibetas (β^{P}, β^{N}, β^{M+}, and β^{M-}) of Bollerslev, Patton, and Quaedvlieg (2022). The monthly betas are estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are presented in parentheses. $\bar{N}$ is the average number of stocks per month and $\bar{R}^2$ is the average R^2 of the monthly cross-sectional predictive regressions.

	Return$_t$				
	(1)	(2)	(3)	(4)	(5)
β^{-}_{t-1}		0.00879***	0.0067***		0.00552***
		(7.22)	(4.12)		(3.64)
β^{Up}_{t-1}	-0.00227***	-0.00212***	-0.00261***		
	(-5.49)	(-4.21)	(-5.97)		
β^{Down}_{t-1}	0.00225***		0.00141**		
	(4.46)		(2.34)		
β^{N}_{t-1}				0.00316**	0.00288**
				(2.21)	(2.01)
β^{P}_{t-1}				-0.00562***	-0.00572***
				(-5.98)	(-6.04)
β^{M+}_{t-1}				0.00049	0.00475**
				(0.27)	(2.13)
β^{M-}_{t-1}				-0.00859***	-0.00378**
				(-7.55)	(-2.5)
Constant	0.01018***	0.0148***	0.0139***	0.01377***	0.01405***
	(5.42)	(8.26)	(8.72)	(8.99)	(9.16)
$\bar{N}$	3831.31	3831.31	3831.31	3831.31	3831.31
$\bar{R}^2$	0.02	0.02	0.03	0.03	0.04

Appendix

Table A.1: Predictive Dependent and Independent Double-Sorted Beta Portfolios on Size, Volatility, Idiosyncratic Volatility, and Illiquidity. This table reports predictive dependent and independent double-sorted portfolio returns for the monthly betas estimated using 1-month window. Panels A, B, C, and D present portfolio returns sorted first by β^- and then by one of the firm-specific characteristics. Panels E, F, G, and H display returns from independent double-sorted portfolios. For high-low portfolios, Newey-West robust t-statistics with four lags are presented in parentheses.

Dependent Sorts

Panel A: β^- then Size

Portfolio	Low Size	P2	P3	P4	High Size	High-Low
Low β^-	1.02%	0.96%	0.96%	0.74%	0.64%	−0.37%
						(−1.52)
P2	1.33%	1.17%	1.16%	0.94%	0.90%	−0.43%
						(−2.33)
P3	1.39%	1.32%	1.20%	1.04%	0.94%	−0.45%
						(−2.51)
P4	1.29%	1.33%	1.16%	1.13%	0.84%	−0.45%
						(−3.04)
High β^-	1.36%	1.16%	1.12%	1.02%	0.90%	−0.45%
						(−3.30)
High - Low	0.34%	0.20%	0.16%	0.28%	0.26%	
	(1.52)	(1.28)	(1.08)	(2.03)	(1.81)	

Panel B: β^- then RV

Portfolio	Low RV	P2	P3	P4	High RV	High-Low
Low β^-	0.92%	0.85%	0.63%	0.17%	−0.37%	−1.29%
						(−3.98)
P2	0.96%	1.02%	1.11%	0.70%	0.10%	−0.86%
						(−2.90)
P3	0.94%	1.04%	1.16%	0.86%	0.60%	−0.34%
						(−1.15)
P4	0.95%	0.94%	0.91%	0.92%	1.04%	0.08%
						(0.33)
High β^-	0.94%	1.05%	0.97%	0.90%	1.05%	0.11%
						(0.50)
High - Low	0.02%	0.20%	0.34%	0.73%	1.42%	
	(0.14)	(1.16)	(1.65)	(3.46)	(5.25)	

Panel C: β^- then IVOL

Portfolio	Low IVOL	P2	P3	P4	High IVOL	High-Low
Low β^-	0.80%	0.82%	0.73%	0.04%	−0.23%	−1.03%
						(−3.23)
P2	0.96%	1.03%	1.05%	0.60%	0.00%	−0.96%
						(−3.22)
P3	0.89%	1.03%	1.17%	0.98%	0.44%	−0.45%
						(−1.67)
P4	0.94%	0.86%	1.10%	0.94%	0.98%	0.04%
						(0.16)
High β^-	0.99%	1.07%	0.89%	0.91%	1.14%	0.15%
						(0.76)
High - Low	0.19%	0.26%	0.16%	0.87%	1.37%	
	(1.32)	(1.41)	(0.78)	(4.39)	(5.22)	

Panel D: β^- then ILLIQ

Portfolio	Low ILLIQ	P2	P3	P4	High ILLIQ	High-Low
Low β^-	0.49%	0.58%	0.59%	0.62%	0.43%	−0.06%
						(−0.36)
P2	0.84%	0.91%	0.88%	1.05%	0.81%	−0.04%
						(−0.24)
P3	0.98%	0.99%	1.04%	1.05%	1.11%	0.13%
						(0.96)
P4	0.83%	1.00%	1.09%	1.15%	1.17%	0.34%
						(2.70)
High β^-	0.93%	0.96%	1.00%	1.08%	1.12%	0.19%
						(1.75)
High - Low	0.44%	0.38%	0.41%	0.46%	0.69%	
	(2.75)	(2.23)	(2.58)	(2.96)	(4.80)	

Independent Sorts

Panel E: β^- and Size

Portfolio	Low Size	P2	P3	P4	High Size	High-Low
Low β^-	0.99%	0.81%	0.75%	0.60%	0.71%	−0.29%
						(−1.30)
P2	1.29%	1.14%	1.00%	0.82%	0.90%	−0.40%
						(−2.08)
P3	1.45%	1.33%	1.17%	1.03%	0.94%	−0.51%
						(−2.63)
P4	1.71%	1.24%	1.28%	1.14%	0.86%	−0.85%
						(−4.18)
High β^-	1.29%	1.39%	1.27%	1.19%	0.92%	−0.37%
						(−2.05)
High - Low	0.30%	0.58%	0.52%	0.59%	0.21%	
	(1.63)	(3.88)	(4.29)	(5.31)	(1.27)	

Panel F: β^- and RV

Portfolio	Low RV	P2	P3	P4	High RV	High-Low
Low β^-	1.05%	1.02%	0.87%	0.75%	0.10%	−0.95%
						(−3.78)
P2	0.99%	1.05%	1.10%	0.93%	0.27%	−0.73%
						(−2.42)
P3	1.00%	0.94%	1.12%	0.80%	0.48%	−0.52%
						(−1.59)
P4	0.93%	0.92%	0.99%	0.91%	0.63%	−0.30%
						(−0.91)
High β^-	1.00%	0.88%	0.98%	1.09%	0.32%	−0.68%
						(−1.72)
High - Low	−0.06%	−0.15%	0.11%	0.34%	0.22%	
	(−0.33)	(−0.89)	(0.65)	(1.53)	(0.59)	

Panel G: β^- and IVOL

Portfolio	Low IVOL	P2	P3	P4	High IVOL	High-Low
Low β^-	0.90%	1.07%	0.78%	0.77%	0.14%	−0.76%
						(−2.73)
P2	0.95%	1.03%	1.04%	0.85%	0.22%	−0.73%
						(−2.38)
P3	0.95%	0.90%	1.07%	0.88%	0.48%	−0.48%
						(−1.55)
P4	0.95%	0.88%	1.02%	0.91%	0.40%	−0.54%
						(−1.43)
High β^-	0.97%	0.93%	1.07%	0.75%	0.58%	−0.39%
						(−1.05)
High - Low	0.07%	−0.14%	0.29%	−0.02%	0.44%	
	(0.43)	(−0.86)	(1.56)	(−0.08)	(1.11)	

Panel H: β^- and ILLIQ

Portfolio	Low ILLIQ	P2	P3	P4	High ILLIQ	High-Low
Low β^-	0.53%	0.42%	0.58%	0.56%	0.59%	0.06%
						(0.29)
P2	0.83%	0.84%	0.86%	0.95%	0.90%	0.06%
						(0.39)
P3	0.97%	0.97%	1.04%	1.02%	1.19%	0.22%
						(1.53)
P4	0.84%	1.02%	1.18%	1.18%	1.11%	0.27%
						(1.97)
High β^-	0.93%	1.05%	1.14%	1.05%	1.15%	0.22%
						(1.27)
High - Low	0.40%	0.62%	0.56%	0.49%	0.56%	
	(2.21)	(3.76)	(3.47)	(2.91)	(3.00)	

Table A.2: Predictive Single-Sorted Beta Portfolios (Quintiles). This table reports predictive single-sorted portfolio returns for the monthly betas estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. For each portfolio, the value-weighted averages for β, β^+, and β^- are reported. Newey-West robust t-statistics with four lags are presented in parentheses.

	Low	P2	P3	P4	High	High - Low
β	0.78%	0.93%	0.93%	1.00%	0.82%	0.04%
	(4.87)	(6.59)	(6.02)	(5.53)	(3.25)	(0.22)
β^-	0.58%	0.83%	0.97%	0.98%	0.92%	0.34%
	(2.64)	(4.08)	(5.05)	(5.69)	(5.89)	(2.61)
β^+	0.89%	0.90%	0.99%	0.96%	0.78%	-0.11%
	(6.24)	(6.21)	(6.31)	(4.92)	(2.97)	(-0.54)

Table A.3: Fama-French 12 Industry Definitions. This table presents the Fama-French 12 industry definitions and number mappings. The definitions and CRSP SIC code matching are obtained from Kenneth R. French's data library.

Industry Number	Industry Definition
1	Consumer Nondurables
2	Consumer Durables
3	Manufacturing
4	Oil, Gas, and Coal Extraction and Products
5	Chemicals and Allied Products
6	Business Equipment
7	Telephone and Television Transmission
8	Utilities
9	Wholesale, Retail, and Some Services (Laundries, Repair Shops)
10	Healthcare, Medical Equipment, and Drugs
11	Finance
12	Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment

Table A.4: Predictive Single-Sorted Beta Portfolios (Monthly). This table reports predictive single-sorted portfolio returns for the monthly betas estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than $1 in the CRSP from 1962 to 2023. For each portfolio, the value-weighted averages for β, β^{+}, and β^{-} are reported. Newey-West robust t-statistics with four lags are presented in parentheses.

Panel A: Stocks sorted by β

Portfolio	Return	t-stat	β	β^{+}	β^{-}
Low	0.68%	(3.29)	−0.95	0.66	−1.65
P2	0.77%	(4.74)	−0.18	0.53	−0.72
P3	0.86%	(5.70)	0.13	0.60	−0.46
P4	0.92%	(6.42)	0.37	0.73	−0.34
P5	0.99%	(6.58)	0.59	0.90	−0.28
P6	0.95%	(5.81)	0.83	1.11	−0.24
P7	0.93%	(5.31)	1.09	1.37	−0.23
P8	1.00%	(5.13)	1.41	1.72	−0.24
P9	0.90%	(4.08)	1.87	2.24	−0.28
High	0.75%	(2.32)	2.82	3.36	−0.40
High - Low	0.08%	(0.33)	3.77	2.70	1.25

Panel B: Stocks sorted by β^{-}

Portfolio	Return	t-stat	β^{-}	β	β^{+}
Low	0.19%	(0.73)	−2.40	−0.64	1.72
P2	0.70%	(2.95)	−1.28	0.18	1.47
P3	0.64%	(2.94)	−0.92	0.48	1.42
P4	0.79%	(3.74)	−0.71	0.68	1.41
P5	0.85%	(4.11)	−0.56	0.81	1.41
P6	0.91%	(4.52)	−0.45	0.92	1.41
P7	1.04%	(5.65)	−0.36	1.01	1.42
P8	0.95%	(5.16)	−0.28	1.08	1.42
P9	0.99%	(5.93)	−0.21	1.13	1.39
High	0.93%	(6.08)	−0.13	1.06	1.24
High - Low	0.74%	(3.70)	2.27	1.69	−0.49

Panel C: Stocks sorted by β^{+}

Portfolio	Return	t-stat	β^{+}	β	β^{-}
Low	0.83%	(6.11)	0.31	−0.09	−0.41
P2	0.88%	(5.76)	0.55	0.19	−0.35
P3	0.88%	(6.07)	0.77	0.43	−0.32
P4	0.94%	(6.19)	0.98	0.65	−0.30
P5	0.95%	(5.91)	1.20	0.86	−0.30
P6	1.04%	(6.27)	1.44	1.08	−0.30
P7	0.94%	(4.96)	1.73	1.33	−0.34
P8	0.96%	(4.34)	2.10	1.64	−0.38
P9	0.90%	(3.74)	2.65	2.08	−0.47
High	0.57%	(1.68)	3.87	2.98	−0.74
High - Low	−0.26%	(−0.91)	3.56	3.07	−0.34

Table A.5: Predictive Single-Sorted Beta Portfolios without Financials. This table reports predictive single-sorted portfolio returns for the monthly betas estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Firms whose SIC codes are between 6000 and 6999 are eliminated. For each portfolio, the value-weighted averages for β, β^+, and β^- are reported. Newey-West robust t-statistics with four lags are presented in parentheses.

Panel A: Stocks sorted by β

Portfolio	Return	t-stat	β	β^+	β^-
Low	0.76%	(4.54)	−0.17	0.33	−0.50
P2	0.86%	(5.69)	0.21	0.41	−0.20
P3	0.87%	(5.98)	0.41	0.55	−0.13
P4	0.89%	(5.94)	0.58	0.70	−0.10
P5	0.93%	(6.02)	0.74	0.85	−0.09
P6	0.90%	(5.35)	0.91	1.01	−0.08
P7	1.05%	(5.83)	1.10	1.20	−0.07
P8	0.95%	(4.80)	1.33	1.43	−0.07
P9	0.86%	(3.42)	1.65	1.77	−0.08
High	0.89%	(2.76)	2.27	2.44	−0.11
High - Low	0.13%	(0.47)	2.44	2.11	0.39

Panel B: Stocks sorted by β^-

Portfolio	Return	t-stat	β^-	β	β^+
Low	0.39%	(1.64)	−0.75	0.13	0.88
P2	0.71%	(3.08)	−0.38	0.55	0.94
P3	0.88%	(3.98)	−0.27	0.73	1.02
P4	0.85%	(4.16)	−0.21	0.83	1.06
P5	1.07%	(5.22)	−0.17	0.93	1.12
P6	0.96%	(5.00)	−0.14	0.97	1.13
P7	0.86%	(4.51)	−0.11	1.02	1.15
P8	0.94%	(5.25)	−0.09	1.05	1.16
P9	0.97%	(5.80)	−0.07	1.07	1.16
High	0.95%	(6.11)	−0.04	1.04	1.10
High - Low	0.56%	(3.12)	0.71	0.91	0.22

Panel C: Stocks sorted by β^+

Portfolio	Return	t-stat	β^+	β	β^-
Low	0.87%	(6.60)	0.27	0.07	−0.20
P2	0.83%	(5.70)	0.47	0.32	−0.14
P3	0.90%	(6.36)	0.63	0.51	−0.11
P4	0.91%	(6.04)	0.79	0.68	−0.09
P5	0.90%	(5.44)	0.94	0.84	−0.09
P6	0.99%	(5.83)	1.11	1	−0.08
P7	1.02%	(5.39)	1.30	1.19	−0.09
P8	0.92%	(4.41)	1.53	1.41	−0.09
P9	0.86%	(3.34)	1.87	1.72	−0.11
High	0.87%	(2.68)	2.54	2.32	−0.15
High - Low	0.00%	(0.01)	2.27	2.25	0.05

Table A.6: Descriptive Statistics. Panel A presents the time-series average of the cross-sectional mean and standard deviation of the monthly beta estimates. Panel B reports average regression coefficients and t-statistics from monthly cross-sectional regressions of β^- on other beta measures. $\bar{R}^2$ is the average R^2 of the monthly cross-sectional regressions. The sample covers common and non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023.

	β^{Up}	β^{Down}	β^{N}	β^{P}	β^{M+}	β^{M-}
Panel A: Cross-Sectional Summary Statistics						
Mean	0.88	0.83	0.63	0.78	0.31	0.23
Median	0.78	0.76	0.56	0.69	0.24	0.17
Std	0.91	1.00	0.37	0.49	0.25	0.24
P25	0.33	0.28	0.36	0.46	0.11	0.10
P75	1.32	1.32	0.82	1.01	0.40	0.30

Panel B: Cross-Sectional Regressions of β^- on other betas

	(1)	(2)	(3)
β^{Up}	0.019***		0.117***
	(4.23)		(4.04)
β^{Down}	0.117***		0.112***
	(21.20)		(3.84)
β^{N}		0.094***	-0.127**
		(18.90)	(-2.39)
β^{P}		0.046***	-0.167***
		(13.21)	(-3.15)
β^{M+}		-0.404***	-0.191***
		(-26.20)	(-3.41)
β^{M-}		-0.627***	-0.396***
		(-38.82)	(-7.22)
$\bar{R}^2$	0.233	0.717	0.731

Table A.7: Predictive Single-Sorted Portfolios on Semibetas. This table reports predictive single-sorted portfolio returns for the monthly semibetas, i.e., (β^P, β^N, β^{M+}, and β^{M-}) of Bollerslev, Patton, and Quaedvlieg (2022). The monthly betas are estimated using 1-month window. The sample covers common and non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. For each portfolio, the value-weighted averages for β, β^+, and β^- are reported. Newey-West robust t-statistics with four lags are presented in parentheses.

Panel A: Stocks sorted by β^P						**Panel B: Stocks sorted by β^N**					
Portfolio	Return	t-stat	β	β^+	β^-	Portfolio	Return	t-stat	β	β^+	β^-
Low	0.92%	(6.76)	0.21	0.35	−0.14	Low	0.84%	(6.58)	0.20	0.36	−0.15
P2	0.98%	(7.01)	0.43	0.55	−0.11	P2	0.88%	(6.30)	0.43	0.56	−0.11
P3	0.89%	(5.97)	0.60	0.71	−0.10	P3	0.92%	(6.30)	0.62	0.73	−0.10
P4	0.96%	(5.95)	0.76	0.87	−0.09	P4	0.94%	(6.20)	0.78	0.88	−0.09
P5	0.96%	(5.86)	0.92	1.03	−0.08	P5	0.94%	(6.05)	0.93	1.04	−0.09
P6	1.02%	(5.77)	1.08	1.19	−0.09	P6	0.99%	(5.49)	1.09	1.20	−0.08
P7	0.92%	(4.59)	1.24	1.37	−0.10	P7	0.96%	(4.77)	1.26	1.38	−0.09
P8	0.80%	(3.75)	1.45	1.59	−0.11	P8	1.01%	(4.54)	1.46	1.60	−0.10
P9	0.94%	(3.75)	1.72	1.89	−0.13	P9	0.77%	(2.88)	1.73	1.89	−0.12
High	0.78%	(2.34)	2.23	2.47	−0.20	High	0.55%	(1.66)	2.22	2.45	−0.18
High - Low	−0.15%	(−0.51)	2.02	2.11	−0.06	High - Low	−0.29%	(−1.04)	2.01	2.09	−0.03
Panel C: Stocks sorted by β^{M+}						**Panel D: Stocks sorted by β^{M-}**					
Portfolio	Return	t-stat	β	β^+	β^-	Portfolio	Return	t-stat	β	β^+	β^-
Low	0.90%	(5.54)	1.11	1.18	−0.05	Low	0.90%	(5.11)	1.17	1.24	−0.05
P2	0.91%	(5.68)	1.04	1.13	−0.07	P2	0.91%	(5.52)	1.06	1.15	−0.06
P3	0.95%	(5.68)	0.98	1.09	−0.09	P3	0.90%	(5.34)	1.00	1.10	−0.08
P4	1.00%	(5.87)	0.95	1.08	−0.10	P4	0.92%	(5.28)	0.94	1.06	−0.09
P5	0.97%	(5.30)	0.92	1.07	−0.13	P5	0.97%	(5.29)	0.91	1.04	−0.12
P6	0.94%	(4.70)	0.90	1.08	−0.15	P6	0.93%	(4.96)	0.87	1.03	−0.14
P7	0.87%	(4.06)	0.88	1.09	−0.19	P7	0.90%	(4.30)	0.83	1.02	−0.17
P8	0.76%	(3.13)	0.87	1.12	−0.24	P8	0.85%	(3.94)	0.80	1.04	−0.22
P9	0.62%	(2.48)	0.82	1.16	−0.32	P9	0.63%	(2.64)	0.74	1.05	−0.30
High	0.21%	(0.74)	0.59	1.17	−0.58	High	0.44%	(1.67)	0.48	1.06	−0.57
High - Low	−0.69%	(−3.34)	−0.52	−0.01	−0.53	High - Low	−0.46%	(−2.48)	−0.69	−0.18	−0.52