A Cross-Sectional Decomposition of Firms' Market Betas*

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Abstract

We introduce a new cross-sectional model that generalizes the CAPM. Using the linear expansion property of covariance, we decompose firms' CAPM betas into negative betas, which capture the negative covariances with other firms in the value-weighted market portfolio and provide a hedge against the market, and positive betas. While the sum of both betas equals market beta, only the negative beta commands a statistically and economically significant risk premium. This finding is robust against existing factors and characteristics, highlighting a distinct dimension of systematic risk and providing a partial explanation for several existing anomalies. The negative beta conceptually and empirically differs from downside beta (Ang et al., 2006a) and semibetas (Bollerslev et al., 2022).

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1 Introduction

The analysis 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. The literature has long considered various interesting generalizations that nest the CAPM. One approach, originating with Kraus and Litzenberger (1976), considers co-movements with higher moments of market returns.[1] Ang et al. (2006b) instead propose a decomposition of market beta and emphasize the importance 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 market semibetas which further disentangle good and bad downside risks.[3]

This paper proposes an alternative decomposition of market beta. At first 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 covariances between the return of the firm and other firms, while the positive market beta contains the positive covariances. 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 from Fama-MacBeth regressions show that like the total market beta, the positive market beta is not statistically or economically significant. However, the negative market beta carries a statistically significant and economically large risk premium of more than eight percent per annum. The average long-short return for the next month based on a decile portfolio sort is 43 basis points, or 5.16% on an annual basis. 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 according to how they hedge against market fluctuations. While in the

[1]See for instance Harvey and Siddique (2000), Dittmar (2002), and Christoffersen et al. (2021) for other contributions to this literature.

[2]See Atilgan et al. (2019), Lettau et al. (2014) and Levi and Welch (2020) for other studies of downside risk.

[3]See Bollerslev et al. (2020a) and Bollerslev et al. (2024) for additional results on the pricing of semibetas.

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 more disaggregated: it is the co-variation between stock i and another stock j at time t.

We verify the robustness of the empirical finding that negative market beta is priced. We show that the economic and statistical significance of the negative beta 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 statistical and economic significance of the negative beta also remains when including the upside and downside betas in Ang et al. (2006a) and the semibetas of Bollerslev et al. (2022). The alpha associated with a factor based on the long-short return on the negative market beta is economically large and is robust to the presence of well-known pricing factors. However, while negative market beta is priced in the presence of these existing characteristics and factors, it is related to several cross-sectional predictors and anomalies. Firms with high negative market beta are larger and less illiquid. They also exhibit less momentum and their returns are less volatile. Because negative market beta is well-motivated by theory and economic intuition, 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 along 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. One possible interpretation of these findings is 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. Savor and Wilson (2013, 2014) argue that the CAPM work well on announcement days because of a more favorable signal to noise ratio.

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, because it relies on entirely different and more disaggregated building blocks. 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 our 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 a semantic resemblance, negative beta is very different from the distinction between separate betas for cash-flow and discount rate news in Campbell and Vuolteenaho (2004), 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 intuition underlying this is completely different.[4] A similar remark holds for the literature on the pricing of good and bad volatility (Bollerslev et al., 2020b; Feunou et al., 2018; Feunou and Okou, 2019). Finally, because our work is related to Ang et al. (2006b) and Bollerslev et al. (2022), it is by extension also related to the vast literature on asymmetric dependencies in stock returns and the pricing of tail risk.[5] However, the link with this literature is much more direct for the exposures proposed by Ang et al. (2006b) and Bollerslev et al. (2022). In short, our approach differs from all this existing work

[4]Bollerslev et al. (2016) and Lee and Wang (2019) decompose the market beta in continuous and discontinuous components.

[5]For important contributions to this literature, see for instance Kraus and Litzenberger (1976), Dittmar (2002), Longin and Solnik (2001), Ang and Chen (2002), Lu and Murray (2019), Elkamhi and Stefanova (2015), Patton (2004), Bali et al. (2009), Engle (2011), Cremers et al. (2015), Kelly and Jiang 2014, Farago and Tédongap, 2018, Engle and Mistry (2014), Farago and Tédongap (2018), Orlowski et al. (2019), and Langlois (2020).

because it is defined in terms of the entire cross-section of co-movements between stocks.

As mentioned above, we do not attempt to fully summarize and cite the existing literature on the cross-section of (stock) returns. 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(s) on the sign and magnitude of the price(s) of risk. Then we discuss the data and we present 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 stock i'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 excess return on the stock 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:

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

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

$$\begin{aligned} \beta_i &= \frac{cov\left(R_i, \sum_{j=1}^{N} w_j R_j\right)}{\sigma_m^2} &\quad (3) \\ &= \sum_{j=1}^{N} \frac{cov(R_i, w_j R_j)}{\sigma_m^2}. &\quad (4) \end{aligned}$$

We use the definition of the market beta in equation (4) to motivate the following decomposition of the market beta of stock i into negative and positive betas associated with stock i, as follows:

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

2.2 Priors on the Price(s) 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^- and β^+ components of total beta to explain and predict the cross-section of stock returns, and to compare the performance of these two components with that of β.[6] 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 together with either β^- or β^+ as characteristics that determine the cross-section of stock returns.[7] It is 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 and either β^- or and β^+ are equivalent (and reduce to the CAPM) if the risk premiums satisfy:

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

Theory does not provide direct guidance regarding the sign and magnitude of the risk premiums λ^-, and λ^+. However, while it is admittedly ad hoc, the null hypothesis in equation (11), a positive price of risk equal to the excess return on the market, is the most interesting one for the empirical analysis of the negative and positive betas. This null hypothesis is also very intuitive. Just as a higher β represents higher risk in the CAPM, a higher (less negative) β^- represents more comovement with (parts of) the market portfolio, and thus more risk. The same is true for β^+.

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

[6]For notational convenience we drop the i subscript notation whenever possible, that is, we use β instead of β_i whenever possible, and a similar remark applies to other exposures.

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

the β^- and β^+ components for pricing and predicting the cross-section, our intuition is that a stock's β^- 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 over time are more valuable and therefore more expensive with a smaller expected return, we expect the stocks that negatively co-move with the cross-section to be most valuable, and therefore to have low expected returns.

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 the 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.

As with any cross-sectional application, we have to choose the window over which we compute the exposures. Our results are robust to the choice of window used for the construction of the betas. In our baseline implementation, we use a one-month window. In Section 4.2 we also report on three- and six-month windows in addition to the baseline one-month window. For the baseline one-month window, at the end of each month we compute β, β^-, and β^+ using daily excess returns during the calendar month. We compute betas every month using daily data and study cross-sectional predictability one month ahead. Perhaps somewhat surprising, this exercise is time-intensive, because it involves recursively computing an N by N matrix.

Panel A of Figure 1 plots the unconditional histogram and Gaussian density fit based on all the positive and negative scaled covariances $cov\left(R_i, w_j R_j\right)/\sigma_m^2$ for all i, j used in the construction of the negative and positive betas in equation (5). These can be thought of as the building blocks of the positive and negative betas. The figure provides some indication of the magnitude of these components. A critical observation is that across the sample, there are a lot of negative comovements between stocks that enter into the computation of the negative betas, but of course there are more positive than negative comovements. The median of the density is at 0.000018, with the 25^{th} percentile at -0.000032 and the 75^{th}

percentile at 0.000059.

Panel B of Figure 1 plots the density of the market β in our sample as well as β^- and β^+. This is once again the unconditional distribution which is based on all estimates of a given exposure across all firms N and times T. Panel A of Table 1 presents 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 of Table 1 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 market 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 negative correlation (-0.05).

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 time-variation in 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 fluctuates a lot in 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 and we discuss the patterns in the long-short returns. Next we present the results of Fama-MacBeth regressions. We document and analyze the relation between negative market beta and other well-known cross-sectional predictors. Finally, we report on the abnormal return after accounting for 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 6. The high-minus-low portfolio based on deciles 1 and 10 generates an economically significant monthly average long-short return of 43 basis points, or 5.16% on an annual basis. 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. Note that this does not mean that β^- does not contain additional information compared to β. 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 is consistent with 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 stylized facts 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 The Dynamics of Long-Short Returns

Panel A of Figure 3 plots the index computed by compounding the monthly value-weighted long-short returns based on β^- decile portfolios 1 and 10. We use a log scale to help with the visual interpretation of this long time series. We omit the time-series for the long-short returns associated with β and β^+ because they are not very informative, but the first three entries in the top panel of Table 3 report 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).[8] We conclude that β^- contains information that is very different from the information in market β, confirming the results from Tables 1 and 2.

Panel A of Figure 3 indicates that the large average long-short β^- return is driven by positive long-short returns during most of the sample period, and extended periods with negative returns are relatively rare. The period between 1980 and 2000 is associated with especially high long-short returns. For comparison, Panel B of Figure 3 plots the cumulative return for the market portfolio. The bursting of the dot-com bubble in 2000 and the financial crisis in 2008 are clearly visible in Panel B, as well as the 1987 market crash and the Covid-19 crisis in 2020, which had a more short-lived impact. The 1973-1974 bear market following the first OPEC crisis also stands out. We highlight these events because the patterns in the β^- long-short return in Panel A are very different, which results in a correlation of -0.187 with the market return in Panel B. Specifically, the impact of the bursting of the dot-com bubble in 2000 is initially very short-lived in the time series in Panel A, followed by a period of high returns and then a long slump. The impact of the 1987 crash is barely discernible, and the 2008 financial crisis leads to a period of high returns after a short-lived decline. The most interesting observation in Panel A of Figure 3 is a protracted period of negative returns in the second half in the 1970s, which is reversed in 1981. This reversal may be due to are changes in monetary policy (the Volcker experiment) and/or the changes in economic policy

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

instituted by the first Reagan administration.

3.3 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 4 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 for β^- in Panel B of Table 2 also emerge in a linear regression 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 4 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 and Table 2 that total β has limited explanatory power 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 associated with β^- is not much affected.[9] The t-statistics are smaller compared to column (2), but the estimates are still highly statistically significant.

3.4 Controlling for Alternative Cross-Sectional Predictors

We now 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

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

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 5 reports the averages of several well-known cross-sectional predictors in the β, β^-, and β^+ decile portfolios from Table 2. We report on the size variable of Banz (1981) and Fama and French (1992), the book-to-market (BTM) 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), and Illiquidity (ILLIQ) (Amihud, 2002; Acharya and Pedersen, 2005)

The descriptive statistics for the β^- decile portfolios in Panel B indicate a (near) monotonic relation between β^- and all of these variables except BTM. It is striking that we do not obtain these monotonic patterns for the β decile portfolios in Panel A. Another striking observation is that the decile portfolios for β^+ in Panel C are also associated with (near) monotonic patterns in MOM, RV, IVOL, and REV. Perhaps more interestingly, we also observe a (near) monotonic pattern for BTM in Panel C, which is not present in Panels A and B.

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 there is no economic intuition for the associated sign; in fact, in some cases such as RV and IVOL economic intuition predicts the opposite sign. Because the sign for the price of risk associated with β^- is consistent with theory and economic intuition, these patterns may suggest that the relation with β^- provides a resolution for important anomalies such as size and volatility.

Another interesting stylized fact regarding the relation between the β^- decile portfolios and these cross-sectional predictors of returns is that the P10 portfolio, which has high returns, consists of large-cap stocks that are also more liquid. This implies that if we want to exploit the resulting cross-sectional patterns, we can do so by going long in stocks that are associated with lower trading costs. For most existing cross-sectional anomalies, such as size, the opposite is the case.

Table 6 further explores the relation between β^- and these alternative cross-sectional predictors through Fama-MacBeth regressions. The column labeled "Univariate" reports on the results of univariate regressions. The controls enter with the expected signs in the univariate regressions, but ILLIQ is not statistically significant. Because of their central place in the literature, the regressions in columns (1)-(6) 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 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 both are statistically significant.

Columns (2)-(6) report on Fama-MacBeth regressions that also contain the other controls (one at a time). 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.

We conclude that β^- is related to several well-known predictors, especially size, (idiosyncratic) variance, and illiquidity. These relations are 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.

3.5 Factors from Cross-Sectional Characteristics

We further explore the relation between β^- and predictors from the existing anomalies literature. Specifically, we elaborate on the findings from Section 3.4 and study the relation between the β^- factor and factors based on the well-known anomalies studied above. The bottom panel of Table 3 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 6. Consistent with our findings from Table 5, the β^- factor is 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. The blue line in Panel A of

Figure 4 plots the (non-cumulative) long-short return for β^-, which is repeated in the other panels. Panels B-E of Figure 4 illustrate the relation between the β^- factor and four highly correlated factors: the ones based on size (Panel B), realized variance (Panel C), idiosyncratic volatility (Panel D), and illiquidity (Panel E). Panel F plots the relation with the momentum factor. Table 3 indicates that this factor is not highly correlated with the β^- factor, and the plot confirms this.

Panels B-E confirm that the β^- factor is related to size, variance, idiosyncratic volatility, 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. Figure 4 clearly illustrates that the β^- factor is related to these four factors. Interestingly, the relation seems particularly strong for size and illiquidity. In contrast, in the FM regressions in Table 4, the relation with the RV characteristic seems stronger than the relation with size and illiquidity.

3.6 Accounting for Factor Models

Table 7 reports the intercepts from the time-series regressions 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. The estimated alphas are statistically significant and range from 41 to 58 basis points, similar in magnitude to the 43 basis points β^- long-short return reported in Table 2. These results confirm that the cross-sectional predictive power of β^- cannot be explained by these factor models.

4 Robustness Analysis and Additional Results

In this section we present a number of robustness analyses. We first report sorting results for quintile portfolios instead of decile portfolios. Next we document the robustness of our results when using alternative estimation windows, and we further explore the relation between β^- and other predictors through bivariate sorts. Next we provide intuition for the performance of β^- by documenting the composition of the portfolios, and we report results for samples obtained using different cross-sectional selection criteria. We also discuss the relation between β^- and downside betas (Ang et al., 2006a) and the semibetas of Bollerslev et al. (2022). Finally we document the impact of the refernce point chosen for the decomposition into positive and negative market beta.

4.1 Quintile Portfolios

Table 8 present the results from univariate sorts based on quintiles rather than deciles. The average return on the β^- 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^- long-short portfolios are also similar. The results for the β and β^+ long-short portfolios are also similar to the ones in Table 2.

4.2 The Beta Estimation Window

Our baseline results in Tables 2 and 4 use estimates of β, β^-, and β^+ 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 9 reports on single sorts for β^-, β, and β^+, using three- and six-month windows of daily data to estimate the betas. The results for β^- 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 baseline estimate of 0.43% (one-month window) changes to 0.62% when using a three-month window and to 0.48% when using a six-month window. This corresponds to annualized long-short returns of 5.16%, 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 and β^+ are consistent with those in Tables 2. The long-short return estimates are not statistically significant and often have the wrong (negative) sign. The return pattern is either hump-shaped or flat.

4.3 Bivariate Portfolio Sorts

We further explore the relation between β^-, β, and β^+. Panel A of Table 10 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 11 further explores the relation between β^- and the other cross-sectional predictors studied in Tables 5 and 6 using double sorts. 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 comparison purposes, Panels A-D first 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 6 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 univariate results in the Fama-MacBeth regressions in Table 6.

Panels E-H present the results from double sorts. We first sort on the competing characteristic and then on β^-.[10] The most important finding is that, except for low-volatility stocks, high β^- is consistently associated with high returns. However, the results for β^- are more economically and statistically significant for small and illiquid stocks, in addition to higher volatility stocks.

[10]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.

4.4 Portfolio Composition

We provide additional insight into the structure and composition of the decile portfolios. First we analyze the dynamics of these portfolios. Table 12 presents the transition matrix. The rows are based on the stocks' portfolio assignments in month t, and the columns represent the portfolios that the stocks transition into in month $t+1$. Each row adds up to 100%. The diagonal indicates a fair amount of persistence for the low (P1) and high (P10) portfolio, and significantly less persistence for the P2-P8 portfolios. When the P1 and P10 stocks transition to another portfolio, they are much more likely to move to portfolios with low and high β^{-}, respectively. More in general, transition probabilities are higher for "nearby" portfolios. Overall, we conclude that the transition matrix supports the cross-sectional predictive power of β^{-}.

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.2 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 the time series of these dominant portfolios for each of the industries, 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^{-} portfolio 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 reliably 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.

4.5 Sample Composition

We also document the robustness of our results to the sample composition. Table A.3 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. However, the average long-short return for β^- exceeds the one in Table 2 and the t-statistic increases. The long-short portfolios for β and β^+ are not significant economically or statistically. Table A.4 reports on a sample that excludes financials. The results for β^- are very similar to the ones in Table 2. Sorting on β and β^+ once again does not yield economically or statistically significant results.

4.6 Equal-Weighted Returns

Table A.5 reports results from univariate sorts using equal-weighted returns. The 10-1 β^- long short portfolio has a statistically significant average return of 54 basis points per month, compared to 43 basis points for value-weighted returns in Table 2. Sorting on β and β^+ once again does not yield economically or statistically significant results.

4.7 Downside Beta and Semibetas

We explore the relation between the negative market beta we propose in this paper and (i) the upside and downside betas of Ang et al. (2006a); (ii) the semibetas of Bollerslev et al. (2022). We consider these cross-sectional predictors separately from the alternative cross-sectional predictors studied in Section 3.4 because they are also based on a decomposition of market beta that sums up to market beta. Because of this feature, downside betas and semibetas are also much more appealing from the perspective of finance theory and economic intuition, as compared to many of the characteristics studied in Section 3.4.

4.7.1 The Models

Because we decompose the market beta, a related concept that comes to mind is the upside and downside beta from Ang et al. (2006a).[11] Bollerslev et al. (2022) further expand this idea and introduce the concept of semibetas. These papers decompose firms' market betas based on the relation between the sign of the firm's return and the sign of the market return at each time t. 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 $R^+_{i,t} = \max(R_{i,t}, 0)$. The differences with our approach are conveniently illustrated by considering the semibetas in Bollerslev et al. (2022), which are defined as follows for firm i:

$$\begin{aligned} \beta_i^{NEG} &= \frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R^-_{i,t}R^-_{m,t}\right) \qquad \beta_i^{POS} = \frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R^+_{i,t}R^+_{m,t}\right) \\ \beta_i^{M+} &= -\frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R^-_{i,t}R^+_{m,t}\right) \quad \beta_i^{M-} = -\frac{1}{\sigma_m^2}\left(\frac{1}{T-1}\sum_{t=1}^{T} R^+_{i,t}R^-_{m,t}\right) \end{aligned} \tag{12}$$

with $\beta_i = \beta_i^{NEG} + \beta_i^{POS} - \beta_i^{M+} - \beta_i^{M-}$. In contrast, our decomposition is given by:

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

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). Intuitively, the semibetas for stock i in equation (12) are defined without reference to the cross-section of stocks $j = 1, ..., N$ that constitute the market portfolio. Instead, the market beta is decomposed by putting the data at each time t into one of four bins, dependent on the sign of the market return and stock i's return. For the negative and positive betas in equation (13) on the other hand, the information at any time t itself is allocated to different

[11] See also Roy (1952), Hogan and Warren (1974) and Bawa and Lindenberg (1977) for important contributions to this literature.

bins on a stock-by-stock basis when computing β_i^- and β_i^+ for a given stock i.

We implement the upside and downside beta of stock i from Ang et al. (2006a) as follows:

$$\begin{aligned} \beta_i^{Up} &= \frac{1}{\sigma_m^{2+}} \left(\frac{1}{T-1} \sum_{t=1}^{T} R_{i,t} R_{m,t}^{+} \right) \\ \beta_i^{Down} &= \frac{1}{\sigma_m^{2-}} \left(\frac{1}{T-1} \sum_{t=1}^{T} R_{i,t} R_{m,t}^{-} \right) \end{aligned} \tag{14}$$

where $\sigma_m^{2+} = \frac{1}{T-1} \sum_{t=1}^{T} \left(R_{m,t}^{+} \right)^2$ and $\sigma_m^{2-} = \frac{1}{T-1} \sum_{t=1}^{T} \left(R_{m,t}^{-} \right)^2$. The implementation of upside and downside beta in the existing literature slightly differs dependent on the definition of the denominator in equation (14), but this has very minor implications for model performance. Our implementation follows Bollerslev et al. (2022). The prior suggested by theory regarding the associated prices of risk λ^{Up} and λ^{Down} is that they are negative and positive respectively.

4.7.2 Empirical Evidence

Table 13 reports on Fama-MacBeth regressions that include β^- in combination with either the upside and/or downside betas from Ang et al. (2006a) or the semibetas from Bollerslev et al. (2022). Panel B of Table A.6 in the Appendix reports descriptive statistics and the results of cross-sectional regressions of β^- on these other betas.

Column (1) of Table 13 indicate that the upside and downside betas from Ang et al. (2006a) are priced in the Fama-MacBeth regressions. The downside beta has the theoretically expected positive sign, and the upside beta has the theoretically expected negative sign. This strong evidence in favor of both upside and downside beta is interesting in itself because the evidence on the pricing of downside beta in the existing literature is mixed. For instance, both Ang et al. (2006a) and Bollerslev et al. (2022) report that only downside beta carries a significant risk premium. However, our main focus is on columns (2)-(3) of Table 13, which indicate that the risk premium on β^- remains positive and statistically significant when including upside and downside beta. The economic and statistical significance is not much affected.

Column (4) of Table 13 reports on Fama-MacBeth regressions with the semibetas of Bollerslev et al. (2022). Our results are overall similar to the findings in Table 2 of Bollerslev et al. (2022), which rely on daily returns. Bollerslev et al. (2022) conclude (page 232): "β^{NEG}

and β^{M-} are associated with statistically significant risk premiums, while β^{POS} and β^{M+} do not appear to be priced in the cross-section." In our sample, the results in column (4) indicate that three of the four semibetas (β^{NEG}, β^{POS}, and β^{M-}) are statistically significant, but the negative sign on β^{POS} is inconsistent with theory.[12] We conclude that similar to the findings of Bollerslev et al. (2022), between the four semibetas our results for β^{M-} are the most robust, statistically significant, and consistent with the theoretical priors.[13]

Our main focus is on the Fama-MacBeth regressions in column (5), which combine the semibetas with β^-. Similar to the results with downside and upside beta in column (3), the loading on β^- remains positive and statistically significant. However, the estimate of the risk premium is somewhat smaller than the univariate estimate in Table 4.[14]

In summary, the results in Table 13 indicate that, consistent with our intuition, the cross-section of β^- contains information that is fundamentally different from the cross-section of downside beta, upside beta, and the semibetas.

4.8 Alternative Decomposition Thresholds

Rather than decomposing the total market beta β_i for firm i into β_i^- and β_i^+ as defined in equation (5), it could be argued that one ought to consider alternative thresholds to decompose the market beta. That is, rather than a decomposition based on the sign of the scaled covariance $cov\left(R_i, w_j R_j\right)/\sigma_m^2$ as in equation (5), the decomposition could be based on whether this covariance exceeds a given fixed threshold. We believe that the zero covariance is the most obvious and interesting threshold to consider, but of course we cannot exclude a priori that other thresholds are priced and generate higher long-short returns. This robustness analysis is somewhat related to the intuition underlying the granular

[12]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 13. However, note that the results for β^{NEG} and β^{POS} are statistically insignificant.

[13]Bollerslev et al. (2020a) 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 negative betas implemented in this paper. The evidence in Table 3 of Bollerslev et al. (2022) confirms that when relying on high-frequency semibetas, β^{NEG} and β^{M-} are priced.

[14]The signs on the semibetas in column (5) are consistent with those in column (4), but the magnitude and statistical significance of the risk premiums associated with β^{M+} and β^{M-} are significantly different. This is consistent with the evidence from Table A.6 that β^- is more strongly cross-sectionally related to β^{M+} and β^{M-}.

betas introduced by Bollerslev et al. (2024), but they consider much more sophisticated refinements.[15]

Figure 6 presents average β^- long-short returns based on various thresholds. The baseline β^- corresponds to the value of zero on the x-axis, which results in a long-short return (on the y-axis) of 43 basis points. First consider the positive thresholds, for which Figure 6 shows an almost monotonic decline in the long-short returns. Note that Figure 6 mainly reports on small thresholds, because these result in cross-sections of both β_i^- and β_i^+ that are computed using large numbers of co-movements with other firms j. In the limit, as the threshold goes to infinity, by definition all firms j are included in the computation of β_i^- and none in the computation of β_i^+. β_i^- therefore becomes equal to the market beta. The y-axis of Figure 6 indicates that this limiting case therefore results in a long-short return of minus six basis points (this corresponds to the average return in Panel A of Table 2). For completeness we also present results for small negative thresholds. The resulting average long-short returns are roughly similar to the results with the zero threshold, but the pattern is not monotonic.

We conclude that it is possible to generate significant long-short returns with β_i^- defined using thresholds other than zero. However, the most interesting conclusion from Figure 6 is that the long-short return declines monotonically when more positive covariances are included in the definition of β^-. Our analysis of course does not address the underlying reasons for this stylized fact. It may be due to an economic mechanism, such as hedging, or to statistical reasons, for example because the estimates based on the resulting cross-sections become more noisy.

5 Conclusion

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

[15]Note that one is in principle also not constrained to decompositions (solely) based on covariances.

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 (Jagannathan and Wang, 1996; 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 decomposition of market beta that is very different from existing decompositions. The framework also generalizes and nests the CAPM. Using the linear expansion property of covariance, we decompose a firm's CAPM beta into two components: a negative beta component, which captures the negative covariances with other firms in the value-weighted market portfolio, and a positive beta, which captures the positive covariances. 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. 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 robust to including other factors and characteristics used in the cross-sectional literature, such as (idiosyncratic) variance, firm size, book-to-market, momentum, and illiquidity. The proposed negative beta also provides an economically plausible (partial) explanation for some of these anomalies.

In future work we plan to investigate the performance of negative beta using international data. Bollerslev et al. (2022) argue that higher frequency data can result in more powerful test of the theory, and implementing the negative betas using intraday data may also prove interesting.

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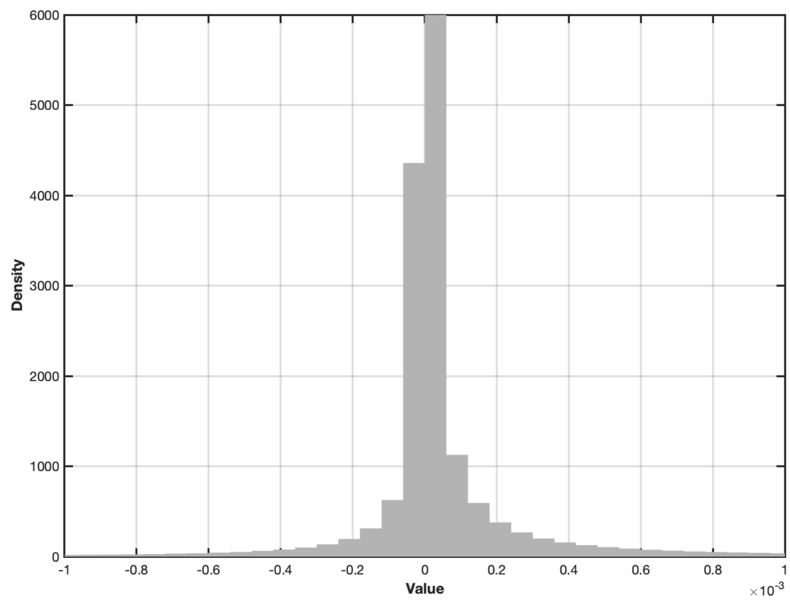
Figure 1: Unconditional Densities of Beta Components and Betas. Panel A plots the histogram of scaled covariances $cov\left(R_i, w_j R_j\right)/\sigma_m^2$ for all i, j used in the construction of the negative and positive betas in equation (5). We use all monthly scaled covariances used in the construction of the positive and negative betas for all stocks over the entire sample to construct the histogram. Panel B plots the unconditional densities of the market beta as well as the negative and positive market betas. We use the betas for all stocks over the entire sample to construct the density.

Panel A: Unconditional Distribution of Beta Components



Panel B: Unconditional Distribution of Betas

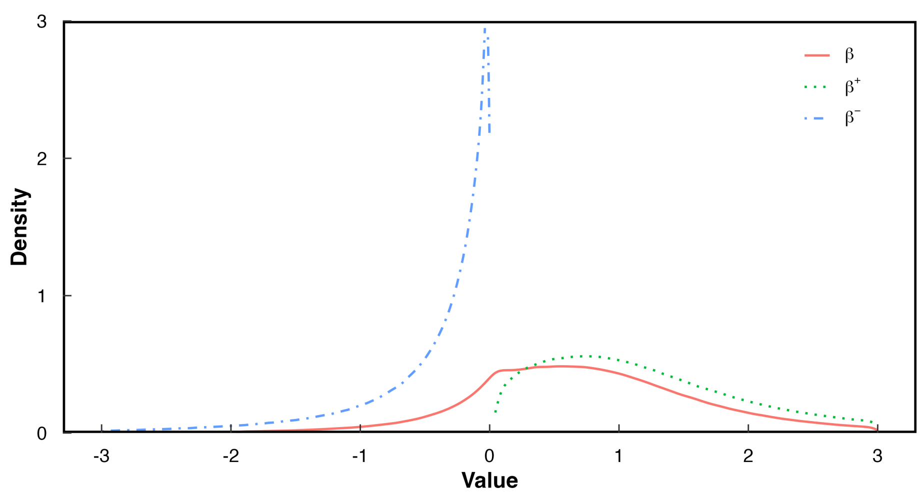
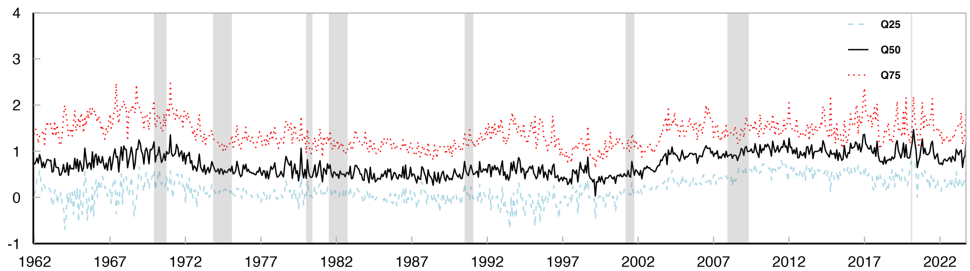
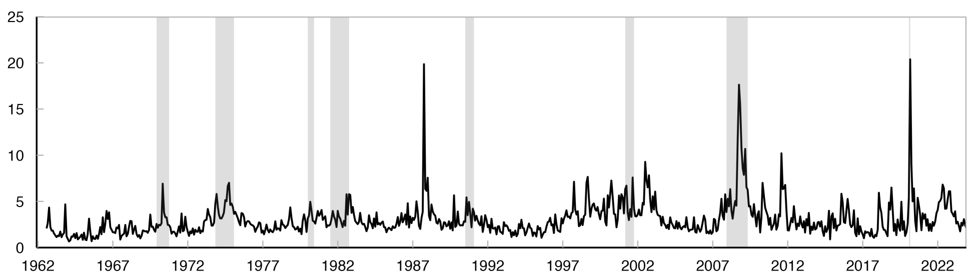


Figure 2: Time Series of Betas. We plot the 25th, 50th, and 75th percentiles of β, β^-, and β^+ for each month. The sample covers common non-penny stocks in the CRSP from 1962 to 2023. Panel B plots the annualized monthly realized volatility of the S&P 500, computed using daily returns. The shaded areas indicate NBER recessions.

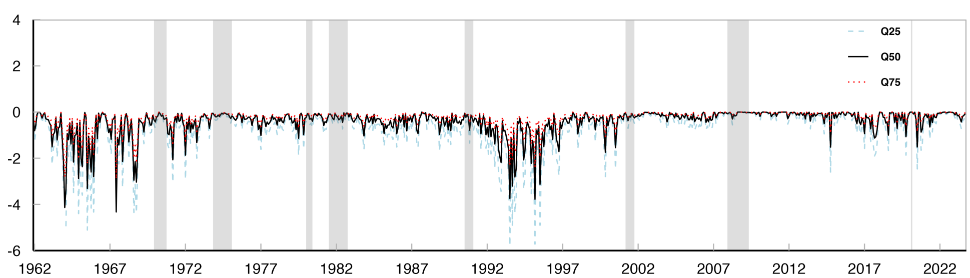
Panel A: β



Panel B: Annualized Market Volatility (%)



Panel C: β^-



Panel D: β^+

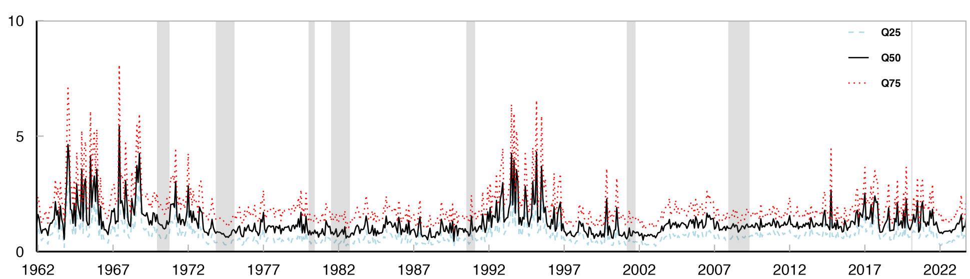


Figure 3: Cumulative Returns of β^{-}, Log Scale. Panel A plots the index from compounding the monthly value-weighted long-short returns based on β^{-} decile portfolios 1 and 10. Panel B plots the index from compounding the market return. Both indexes are represented in log scale. The shaded areas indicate NBER recessions.

Panel A: β^{-}

Panel B: Market Return

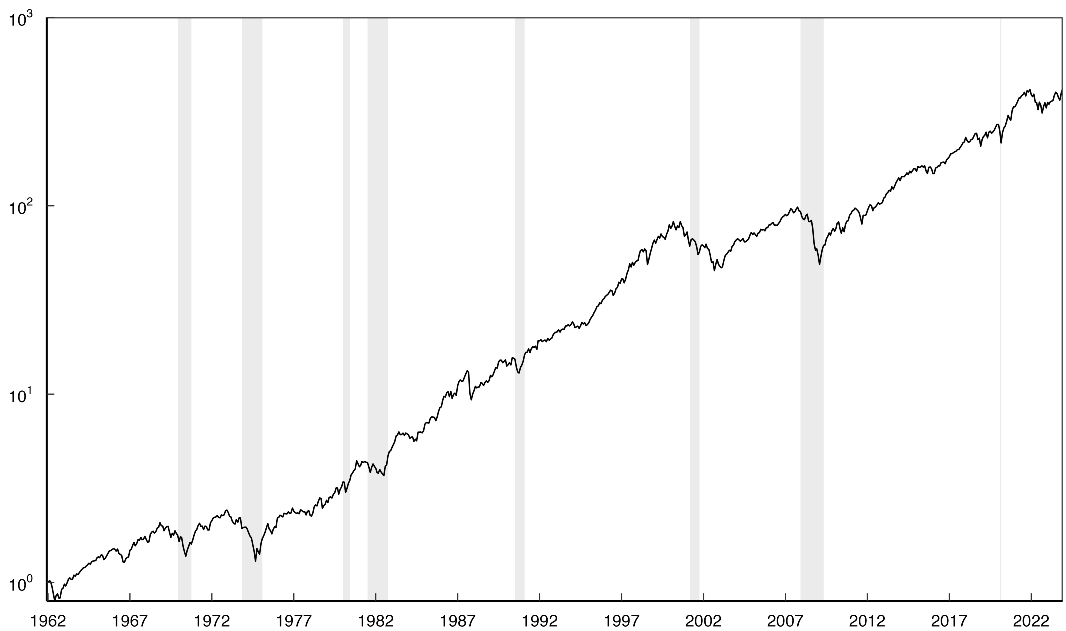
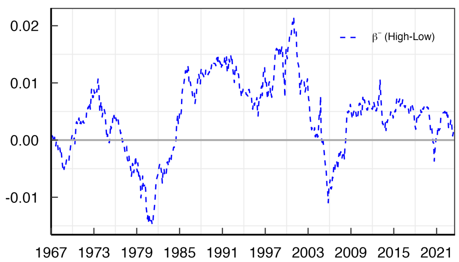
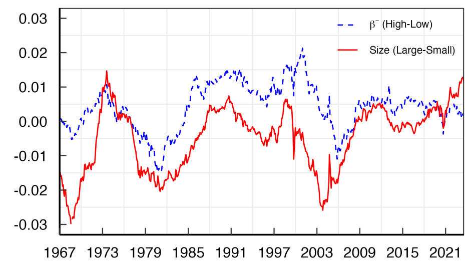


Figure 4: Moving Averages of Monthly Long-Short Returns. We plot the 60-month moving averages of monthly long-short portfolio returns based on various characteristics. RV stands for realized variance, the sum of daily squared returns over a month. IVOL is idiosyncratic volatility, MOM is momentum, and ILLIQ is Amihud's illiquidity measure.

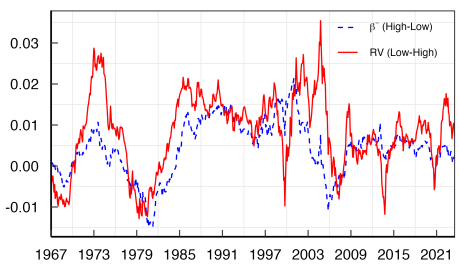
Panel A: β^-



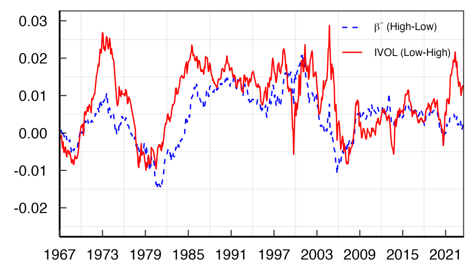
Panel B: β^- and Size



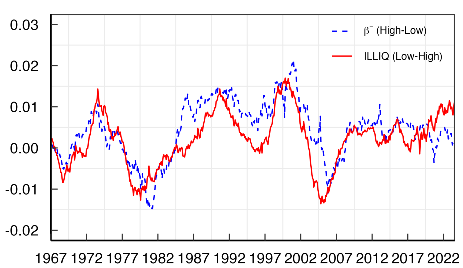
Panel C: β^- and RV



Panel D: β^- and IVOL



Panel E: β^- and ILLIQ



Panel F: β^- and MOM

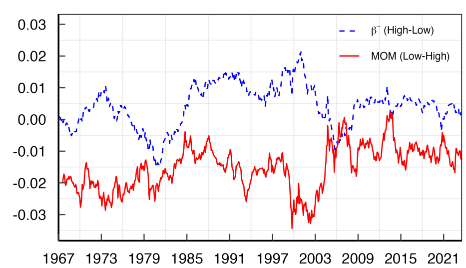


Figure 5: Industry Representation in the β^- Portfolios. We plot a time-series heatmap based on the 12 Fama-French industries. We identify the dominant β^- portfolio for each industry-year based on the highest share of an industry's stocks representation relative to the number of stocks in portfolio,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

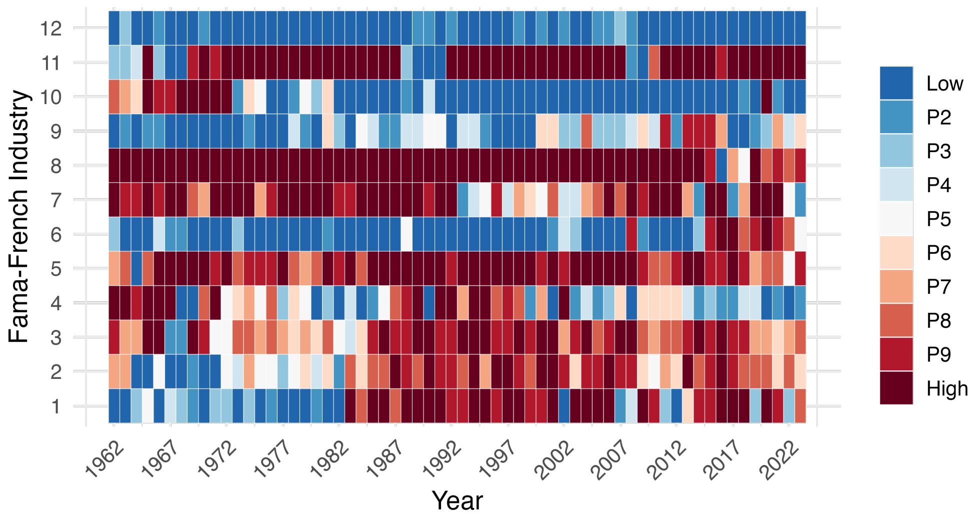


Figure 6: β^- Long-Short Returns for Alternative Decomposition Thresholds. We plot the average β^- long-short return as a function of the threshold used to decompose the market betas. In the limit, we retrieve the long-short return corresponding to the total market beta.

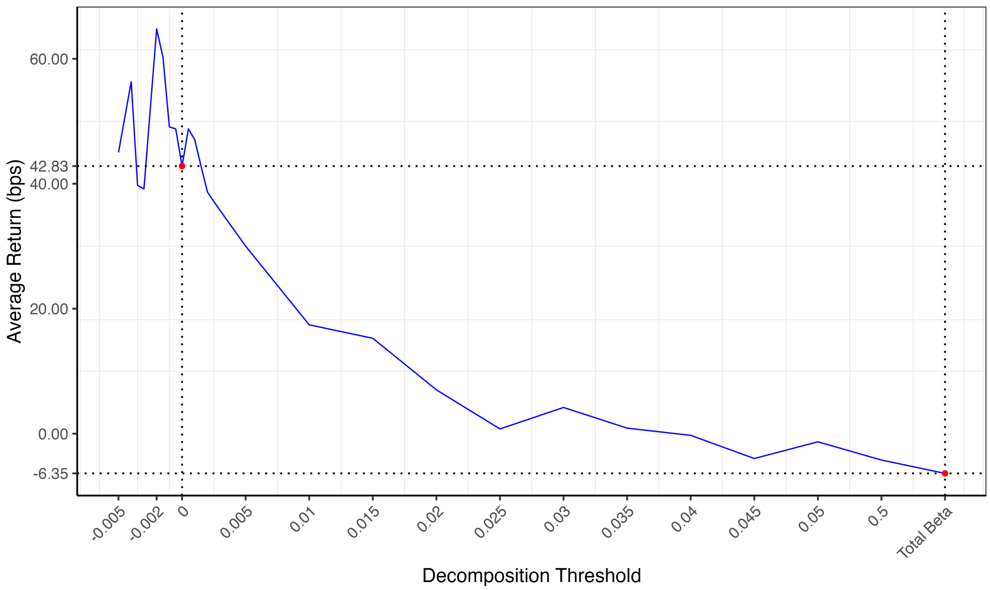


Table 1: Descriptive Statistics. Panel A reports the time-series average of the cross-sectional means and standard deviations of the monthly beta estimates. Panel B reports the cross-sectional correlation between the three betas. The sample covers common non-penny stocks with prices higher than \$5 in 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. We report predictive single-sorted decile portfolio returns associated with β, β^+, and β^-. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are 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: Factor Correlations. We report correlations between factors constructed as monthly long-short portfolio returns. Portfolios bet against β and β^{+}. $R_m - R_f$, SMB, and HML are obtained from Kenneth R. French's data library. Statistically significant factor correlations at 5% level are bolded.

	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
β^{-}	1	**-0.187**	**-0.599**	**0.209**	**-0.086**	**-0.556**	**-0.649**	-0.026	**-0.273**
$R_m - R_f$		1	**0.296**	**-0.202**	**-0.125**	**0.592**	**0.506**	**-0.268**	**-0.275**
SMB			1	**-0.160**	0.019	**0.587**	**0.689**	**-0.120**	**0.399**
HML				1	**-0.231**	**-0.396**	**-0.377**	0.006	**0.298**
MOM					1	-0.028	-0.056	**0.292**	**-0.158**
RV						1	**0.941**	**-0.139**	**0.084**
IVOL							1	**-0.122**	0.001
REV								1	-0.042
ILLIQ									1

Table 4: Fama-MacBeth Regressions. We report the results of Fama-MacBeth cross-sectional predictive regressions of stock returns on betas. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common 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 5: Decile Portfolios. Descriptive Statistics and Composition. We report the average characteristics associated with the single-sorted beta portfolios. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. The BTM variable is the natural logarithm of the average. $ILLIQ$ is multiplied by 10^6. $Size$ is in millions of dollars.

Panel A: Stocks sorted by β

Portfolio	Size	BTM	MOM	RV	IVOL	REV	ILLIQ
Low	$19,305$	-0.44	0.19	0.02	0.02	0.03	0.64
P2	$32,979$	-0.36	0.15	0.01	0.01	0.01	0.22
P3	$41,349$	-0.35	0.15	0.01	0.01	0.01	0.14
P4	$45,411$	-0.34	0.14	0.01	0.01	0.01	0.11
P5	$48,300$	-0.35	0.15	0.01	0.01	0.01	0.07
P6	$50,119$	-0.40	0.15	0.01	0.01	0.01	0.06
P7	$63,995$	-0.45	0.17	0.01	0.01	0.01	0.05
P8	$63,658$	-0.49	0.19	0.01	0.01	0.01	0.04
P9	$49,281$	-0.51	0.23	0.01	0.02	0.02	0.05
High	$34,288$	-0.51	0.34	0.03	0.02	0.03	0.10

Panel B: Stocks sorted by β^-

Portfolio	Size	BTM	MOM	RV	IVOL	REV	ILLIQ
Low	$13,197$	-0.58	0.27	0.05	0.04	0.06	0.98
P2	$20,167$	-0.53	0.23	0.02	0.03	0.03	0.43
P3	$28,124$	-0.43	0.20	0.02	0.02	0.02	0.30
P4	$31,518$	-0.43	0.20	0.02	0.02	0.02	0.19
P5	$37,579$	-0.42	0.20	0.01	0.02	0.02	0.15
P6	$45,397$	-0.41	0.19	0.01	0.02	0.02	0.10
P7	$48,602$	-0.43	0.18	0.01	0.01	0.01	0.07
P8	$56,513$	-0.44	0.18	0.01	0.01	0.01	0.04
P9	$62,338$	-0.46	0.17	0.01	0.01	0.01	0.03
High	$71,758$	-0.49	0.16	0.01	0.01	0.01	0.01

Panel C: Stocks sorted by β^+

Portfolio	Size	BTM	MOM	RV	IVOL	REV	ILLIQ
Low	$26,546$	-0.34	0.15	0.01	0.01	0.01	0.28
P2	$39,569$	-0.34	0.14	0.01	0.01	0.01	0.16
P3	$49,101$	-0.38	0.14	0.01	0.01	0.01	0.12
P4	$48,868$	-0.37	0.15	0.01	0.01	0.01	0.10
P5	$48,987$	-0.40	0.15	0.01	0.01	0.01	0.07
P6	$56,528$	-0.45	0.17	0.01	0.01	0.02	0.07
P7	$62,210$	-0.49	0.18	0.01	0.01	0.02	0.06
P8	$51,889$	-0.51	0.21	0.01	0.02	0.02	0.06
P9	$46,212$	-0.53	0.27	0.02	0.02	0.02	0.08
High	$31,328$	-0.54	0.38	0.04	0.03	0.04	0.18

Table 6: Fama-MacBeth Regressions with Controls. We report the results of Fama-MacBeth cross-sectional predictive regressions of stock returns on betas and other controls. The controls include size (Size), book-to-market (btm), realized variance (RV), idiosyncratic volatility (IVOL), Amihud's illiquidity (ILLIQ), momentum (MOM), and reversal (REV). The data frequency is monthly and the monthly betas, realized variance, idiosyncratic volatility, and illiquidity are computed using a 1-month window. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are 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)
Constant		0.03019***	0.02469***	0.03072***	0.0371***	0.02936***	0.03362***
		(4.45)	(3.84)	(4.74)	(6.15)	(4.29)	(4.7)
β^-_{t-1}	0.00715***	0.00621***	0.00579***	0.00354***	0.00332**	0.00439***	0.00589***
	(6.74)	(5.92)	(5.6)	(2.75)	(2.17)	(4.04)	(6.51)
$\log(\text{Size})_{t-1}$	-0.00055*	-0.00095***	-0.00086***	-0.00099***	-0.00131***	-0.00083**	-0.00093***
	(-1.90)	(-2.8)	(-2.63)	(-3.04)	(-4.34)	(-2.43)	(-2.73)
$\log(\text{btm})_{t-1}$	0.00144***	0.00138***	0.0014***	0.00123***	0.00102**	0.00144***	0.00133***
	(3.32)	(3.15)	(3.45)	(2.92)	(2.54)	(3.26)	(3.04)
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)
$\bar{N}$		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

Table 7: Abnormal Returns. Various Factor Models. We run time-series regressions of monthly long-short portfolio returns on β^- on the factors in the following models: the CAPM, the Fama-French 3-factor model (FF3), the Fama-French 3-factor model plus the Carhart momentum factor (FF3+MOM), and the Fama-French 5-factor model. The Fama-French factor portfolio returns are obtained from Kenneth R. French's data library. $\hat{\alpha}$ is the estimate of the intercept estimate in the time-series regression. Newey-West robust t-statistics are 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 Single-Sorted Quintile Beta Portfolios. We report predictive single-sorted quintile portfolio returns associated with β, β^{+}, and β^{-}. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are 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 9: Predictive Single-Sorted Beta Portfolios. Alternative Beta Windows. We report predictive single-sorted decile portfolio returns associated with β, β^{+}, and β^{-}. The data frequency is monthly and the betas are estimated using either a three-month or a six-month window. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are in parentheses.

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 10: Predictive Double-Sorted Beta Portfolios. We report predictive double-sorted quintile portfolio returns. The data frequency is monthly and the betas are estimated using a one-month window. The sample covers common non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. For the high-low portfolios, Newey-West robust t-statistics with four lags are 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%	0.09%
						(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 11: Predictive Single- and Double-Sorted Beta Portfolios. β^-, Size, Volatility, Idiosyncratic Volatility, and Illiquidity. We report predictive single- and double-sorted portfolio returns. The data frequency is monthly and the betas are estimated using a one-month window. The sample covers common non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. For the high-low portfolios, Newey-West robust t-statistics with four lags are 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 12: β^- **Transition Matrix.** We present the transition matrix for the β^- decile portfolios. The rows are based on the stocks' portfolio assignments in month t, and the columns represent the portfolios that the stocks transition into 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 13: Fama-MacBeth Regressions. Downside Betas and Semibetas. We report the results of Fama-MacBeth cross-sectional predictive regressions of stock returns on various exposures (betas). The data frequency is monthly and the betas are estimated using a 1-month window. We consider negative beta β^{-}, the β^{Up} and β^{Down} of Ang, Li, and Xing (2006), and the monthly semibetas (β^{POS}, β^{NEG}, β^{M+}, and β^{M-}) of Bollerslev, Patton, and Quaedvlieg (2022). The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are 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^{NEG}_{t-1}				0.00316**	0.00288**
				(2.21)	(2.01)
β^{POS}_{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 Double-Sorted Beta Portfolios. β^-, Size, Volatility, Idiosyncratic Volatility, and Illiquidity. Dependent and Independent Double Sorts. We report predictive dependent and independent double-sorted portfolio returns. The data frequency is monthly and the betas are estimated using a one-month window. Panels A, B, C, and D present portfolio returns sorted first on β^- and then on one of the firm-specific characteristics. Panels E, F, G, and H display returns from independent double-sorted portfolios. For the high-low portfolios, Newey-West robust t-statistics with four lags are 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: The Fama-French Twelve Industries. 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.3: Predictive Single-Sorted Beta Portfolios. Sample Selection Based on \$1 Stock Price. We report predictive single-sorted decile portfolio returns associated with β, β^+, and β^-. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common non-penny stocks with prices higher than \$1 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are 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.4: Predictive Single-Sorted Beta Portfolios. Excluding Financials We report predictive single-sorted decile portfolio returns associated with β, β^{+}, and β^{-}. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common 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 excluded from the sample. Newey-West robust t-statistics with four lags are 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.5: Predictive Single-Sorted Beta Portfolios. Equal Weights We report predictive single-sorted equal-weighted decile portfolio returns associated with β, β^+, and β^-. The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common non-penny stocks with prices higher than $5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are in parentheses.

Panel A: Stocks sorted by β^-						**Panel B: Stocks sorted by β^+**					
Portfolio	Return	t-stat	β^-	β	β^+	Portfolio	Return	t-stat	β^+	β	β^-
Low	0.43%	(1.70)	−1.91	−0.30	1.59	Low	1.02%	(6.65)	0.27	−0.23	−0.51
P2	0.81%	(3.33)	−0.99	0.53	1.54	P2	1.08%	(6.08)	0.53	−0.02	−0.56
P3	0.91%	(3.80)	−0.73	0.81	1.58	P3	1.10%	(6.03)	0.74	0.18	−0.55
P4	1.01%	(4.30)	−0.58	0.96	1.59	P4	1.13%	(5.82)	0.93	0.37	−0.54
P5	1.06%	(4.63)	−0.47	1.06	1.59	P5	1.13%	(5.65)	1.13	0.56	−0.55
P6	1.17%	(5.33)	−0.39	1.11	1.56	P6	1.15%	(5.32)	1.36	0.76	−0.56
P7	1.21%	(5.74)	−0.32	1.13	1.51	P7	1.11%	(4.81)	1.62	1.00	−0.58
P8	1.22%	(6.07)	−0.26	1.12	1.44	P8	1.01%	(4.09)	1.96	1.29	−0.61
P9	1.17%	(6.12)	−0.20	1.07	1.32	P9	0.89%	(3.21)	2.45	1.71	−0.66
High	1.11%	(6.85)	−0.12	0.87	1.04	High	0.48%	(1.44)	3.77	2.77	−0.87
High - Low	0.68%	(4.45)	1.79	1.18	−0.55	High - Low	−0.54%	(−2.13)	3.50	2.99	−0.36

Table A.6: Descriptive Statistics. Downside Beta and Semibetas. Panel A presents the time-series averages of the cross-sectional mean and standard deviation for the semibetas (β^{POS}, β^{NEG}, β^{M+}, and β^{M-}) of Bollerslev, Patton, and Quaedvlieg (2022) and the β^{Up} and β^{Down} of Ang, Li, and Xing (2006). The data frequency is monthly and the betas are estimated using a 1-month window. Panel B reports average regression coefficients and t-statistics from monthly cross-sectional regressions of β^{-} on downside betas and semibetas. $\bar{R}^2$ is the average R^2 of the monthly cross-sectional regressions. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023.

	β^{Up}	β^{Down}	β^{NEG}	β^{POS}	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^{NEG}		0.094***	-0.127**
		(18.90)	(-2.39)
β^{POS}		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. Downside Beta and Semibetas. We report predictive single-sorted decile portfolio returns for the semibetas (β^{POS}, β^{NEG}, β^{M+}, and β^{M-}) of Bollerslev, Patton, and Quaedvlieg (2022) and the β^{Up} and β^{Down} of Ang, Li, and Xing (2006). The data frequency is monthly and the betas are estimated using a 1-month window. The sample covers common non-penny stocks with prices higher than \$5 in the CRSP from 1962 to 2023. Newey-West robust t-statistics with four lags are in parentheses.

Panel A: Stocks sorted by β^{POS}

Portfolio	Return	t-stat	β	β^+	β^-
Low	1.05%	(7.18)	0.07	0.46	−0.38
P2	1.01%	(6.96)	0.30	0.65	−0.33
P3	0.99%	(6.41)	0.50	0.83	−0.30
P4	0.97%	(6.39)	0.68	1.00	−0.28
P5	0.92%	(5.64)	0.86	1.17	−0.28
P6	0.85%	(4.92)	1.04	1.38	−0.28
P7	0.91%	(4.76)	1.25	1.61	−0.30
P8	0.95%	(4.59)	1.49	1.90	−0.34
P9	0.79%	(3.35)	1.84	2.33	−0.40
High	0.63%	(2.02)	2.57	3.28	−0.58
High - Low	−0.42%	(−1.72)	2.50	2.82	−0.21

Panel B: Stocks sorted by β^{NEG}

Portfolio	Return	t-stat	β	β^+	β^-
Low	0.72%	(5.16)	0.08	0.51	−0.43
P2	0.78%	(5.50)	0.33	0.69	−0.35
P3	0.88%	(6.04)	0.54	0.87	−0.31
P4	0.89%	(5.70)	0.71	1.03	−0.29
P5	0.97%	(6.15)	0.89	1.21	−0.28
P6	1.02%	(6.00)	1.06	1.39	−0.28
P7	0.99%	(5.17)	1.26	1.61	−0.29
P8	0.96%	(4.58)	1.50	1.89	−0.32
P9	0.89%	(3.60)	1.82	2.28	−0.37
High	0.72%	(2.25)	2.46	3.09	−0.50
High - Low	0.00%	(−0.02)	2.38	2.58	−0.07

Panel C: Stocks sorted by β^{M+}

Portfolio	Return	t-stat	β	β^+	β^-
Low	0.79%	(4.61)	1.20	1.44	−0.17
P2	0.92%	(5.47)	1.12	1.38	−0.21
P3	0.93%	(5.49)	1.06	1.35	−0.25
P4	0.94%	(5.38)	0.99	1.33	−0.29
P5	0.94%	(5.35)	0.92	1.31	−0.34
P6	1.04%	(5.65)	0.85	1.29	−0.41
P7	0.98%	(5.01)	0.78	1.30	−0.48
P8	0.94%	(4.40)	0.69	1.33	−0.60
P9	0.81%	(3.61)	0.56	1.37	−0.78
High	0.67%	(2.77)	0.15	1.48	−1.32
High - Low	−0.12%	(−0.69)	−1.05	0.05	−1.15

Panel D: Stocks sorted by β^{M-}

Portfolio	Return	t-stat	β	β^+	β^-
Low	1.05%	(5.71)	1.31	1.56	−0.19
P2	0.98%	(5.68)	1.18	1.45	−0.21
P3	0.96%	(5.62)	1.09	1.38	−0.23
P4	0.91%	(5.48)	1.01	1.32	−0.26
P5	0.79%	(4.65)	0.93	1.28	−0.30
P6	0.88%	(4.97)	0.86	1.25	−0.35
P7	0.83%	(4.56)	0.77	1.23	−0.43
P8	0.81%	(4.25)	0.68	1.23	−0.52
P9	0.78%	(3.75)	0.52	1.24	−0.70
High	0.43%	(1.80)	0.08	1.35	−1.27
High - Low	−0.62%	(−3.97)	−1.23	−0.21	−1.08

Panel E: Stocks sorted by β^{Up}

Portfolio	Return	t-stat	β	β^+	β^-
Low	0.92%	(4.87)	−0.23	0.73	−0.97
P2	1.00%	(5.90)	0.16	0.67	−0.51
P3	1.04%	(7.02)	0.34	0.73	−0.37
P4	0.93%	(6.23)	0.51	0.84	−0.30
P5	0.93%	(6.14)	0.69	0.99	−0.27
P6	0.97%	(5.80)	0.87	1.16	−0.25
P7	0.88%	(4.93)	1.08	1.37	−0.25
P8	0.92%	(4.73)	1.33	1.65	−0.25
P9	0.86%	(3.99)	1.69	2.06	−0.29
High	0.70%	(2.40)	2.45	3.00	−0.43
High - Low	−0.22%	(−1.09)	2.68	2.27	0.54

Panel F: Stocks sorted by β^{Down}

Portfolio	Return	t-stat	β	β^+	β^-
Low	0.60%	(3.22)	−0.23	0.80	−1.05
P2	0.72%	(4.80)	0.21	0.73	−0.52
P3	0.76%	(5.15)	0.41	0.80	−0.37
P4	0.86%	(5.77)	0.57	0.90	−0.30
P5	0.86%	(5.68)	0.73	1.03	−0.26
P6	1.02%	(6.42)	0.91	1.20	−0.24
P7	0.94%	(5.33)	1.12	1.41	−0.24
P8	1.03%	(5.34)	1.36	1.68	−0.25
P9	0.95%	(4.26)	1.71	2.08	−0.28
High	0.82%	(2.70)	2.39	2.88	−0.38
High - Low	0.22%	(1.06)	2.62	2.08	0.67