Is the asymmetry of systematic risk-taking by investors and its dispersion a pricing factor ?

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1 Motivation

The Capital Asset Pricing Model (CAPM) has long been considered the most widely studied and practically applied model in the field of asset pricing. Its basic form predicts a simple linear relationship between the expected excess return of an asset and its beta relative to the entire market portfolio. Early empirical studies broadly confirmed this prediction. However, subsequent literature has questioned the explanatory power of standard market beta in explaining the cross-sectional variation in expected returns. Research by Frazzini & Pedersen (2014) suggests that market beta possesses unique asset pricing abilities. Taking long positions in stocks with low market beta and short positions in stocks with high market beta can lead to significantly positive risk-adjusted returns. Bollerslev et al. (2016), decomposing beta into continuous and discontinuous components, finds that intraday discontinuous beta brings about significant risk premiums, while intraday continuous beta does not.

Considering investors' distinct concerns about downside losses and upside gains, Farago & Tédongap (2018) found that an asset pricing model with disappointment aversion and changing macroeconomic uncertainty, three disappointment-related factors, in addition to market returns and volatility, impact asset pricing, Ang, Chen, & Xing (2006) discovers that investors emphasizing downside risk require additional risk premiums for holding stocks with high downside beta. Building upon this, Bollerslev et al. (2022) combines the research on realized covariance decomposition by Bollerslev, Li, Patton, & Quaedvlieg (2020a). Based on the positive and negative relationship between stock returns and market index returns, they decompose realized beta into four different realized semi-betas. They find that two semi-betas generated by negative market return covariance exhibit significant pricing abilities. Simultaneously, Bollerslev, Li, & Zhao (2020) finds a strong pricing effect in the short term (e.g., one week) when decomposing "good volatility" and "bad volatility" based on the positive and negative returns of stock. This highlights investors' sensitivity differences to the two distinct states of stock movements, indicating a significant impact of different upward and downward states of assets on investor decisions. As market indices serve as the most closely monitored assets by investors and are widely used in portfolio comparison and risk management, the impact of market indices being in different upward or downward states is inevitably more pronounced for investors compared to individual stocks. Moreover, investors' different perceptions of systematic risk in various states may be an important source of risk or pricing.

Furthermore, studies on whether and to what extent market beta can explain differences in cross-sectional asset returns implicitly assume its constancy throughout the day. Andersen et al. (2021), by employing new econometric tools, tests the hypothesis of constant intraday beta and significantly rejects it. This implies that beta is not constant throughout the day. With the availability of high-frequency data, the increasing attention to intraday variations in beta raises concerns. If market beta does exhibit significant intraday fluctuations, the traditional assumption of "beta stability" in research may no longer hold, affecting our understanding of the relationship between beta and stock pricing.

In summary, the core of this study, based on relaxing the assumption of constant intraday beta, lies in examining the magnitude of systematic risk differences borne by investors in the market index under different market conditions. Additionally, it investigates whether the intraday stability of these differences can effectively explain variations in cross-sectional stock returns. This perspective is crucial in filling the gap in the current academic literature regarding the relationship between market beta and stock pricing. By focusing on how investors perceive and react to systematic risk under different market conditions, the study offers a key perspective that contributes to a more comprehensive understanding of investors' sensitivity to systematic risk during market fluctuations. This contributes to a deeper understanding of the differences in cross-sectional stock returns. Given that investors may exhibit different risk preferences and behavioral reactions under varying market conditions, understanding the risk characteristics of the market index during different periods allows investors and asset managers to more flexibly adjust their portfolios to adapt to dynamic market changes. This, in turn, enhances risk-adjusted returns. Overall, this research is of significant importance in advancing the theory of stock market pricing and providing a more scientific basis for investment decision-making.

The subsequent sections of the article are organized as follows: Section 2 elaborates on the theoretical foundation and construction methods of semi-beta differences under different market states and their degree of dispersion. Section 3 introduces the data and variables used in the empirical study. Section 4 conducts portfolio sorting analysis, presenting the results of univariate and bivariate sorting. Section 5 applies Fama-Macbeth regression to further examine whether our core variables of interest possess significant risk premiums. Section 6 applies a series of beta-related factors to construct investment strategies and backtests strategy performance, clarifying the economic value of our newly proposed core variables. Section 7 presents robustness tests. Section 8 concludes the article, providing a summary.

2 Intraday Semi-betas variation in different market situation

2.1 Definitions

Consider a bivariate Itô semimartingale log-price process $Z_t = (X_t, Y_t)^\top$, represented as:

$$\boldsymbol{Z}_t = \boldsymbol{Z}_0 + \int_0^t \boldsymbol{b}_s ds + \int_0^t \boldsymbol{\sigma}_s d\boldsymbol{W}_s + \boldsymbol{J}_t \tag{1}$$

Here, X_t and Y_t are the logarithmic price vectors of the index and stock at time t, $\boldsymbol{b}_s$ is a drift process taking values in $\mathbb{R}^2$, W_s is a two-dimensional standard Brownian motion, σ_s is a 2×2 random volatility matrix, and J_t is a pure jump process. Assuming that intra-day prices of the two assets are available at m equally spaced time points within the trading day $[t, t+1]$, where m is the theoretical data quantity on day t at the given data sampling frequency, following Barndorff-Nielsen & Shephard (2004), the variance-covariance matrix of $\boldsymbol{Z}_t$ can be expressed as:

$$\mathbf{RCOV}_t \equiv \sum_{k=1}^{m} \mathbf{r}_{t,k}\mathbf{r}'_{t,k} \xrightarrow{\mathbb{P}} \int_{t-1}^{t} \boldsymbol{\sigma}_s\boldsymbol{\sigma}'_s + \sum_{\mathrm{t-1 \le s \le t}} \boldsymbol{J}_s\boldsymbol{J}'_s$$

Here, $\mathbf{r}_{t,k} = \mathbf{Z}_{t+k/m} - \mathbf{Z}_{t+(k-1)/m}$ represents the logarithmic discrete-time return vector for the k-th interval on day t. Now, using $\mathbf{r}^+_{t,k}$ and $\mathbf{r}^-_{t,k}$ to denote the corresponding positive and negative high-frequency return vectors, following the decomposition method of Bollerslev, Li, Patton, & Quaedvlieg (2020b) (hereafter referred to as BLPQ), four realized semi-variance-covariance matrices can be defined simply as:

$$\mathbf{P}_t \equiv \sum_{k=1}^{m} \mathbf{r}^+_{t,k}\mathbf{r}^{+\,\prime}_{t,k}, \quad \mathbf{N}_t \equiv \sum_{k=1}^{m} \mathbf{r}^-_{t,k}\mathbf{r}^{-\prime}_{t,k}, \quad \mathbf{M}^+_t \equiv \mathbf{M}^{-\prime}_t \equiv \sum_{k=1}^{m} \mathbf{r}^+_{t,k}\mathbf{r}^{-\prime}_{t,k}$$

Specifically, $\mathbf{r}^+_{t,k} = \mathbf{r}_{t,k} \odot \mathbf{I}^+_{t,k}$ $\quad \mathbf{r}^-_{t,k} = \mathbf{r}_{t,k} \odot \mathbf{I}^-_{t,k}$, where $\odot$ denotes the Hadamard product (element-wise multiplication), $\mathcal{I}^+_{t,k} \equiv \left[1_{\{r_{t,k,x}>0\}}, 1_{\{r_{t,k,y}>0\}}\right]'$, $\mathcal{I}^-_{t,k} \equiv \left[1_{\{r_{t,k,x}\leq 0\}}, 1_{\{r_{t,k,y}\leq 0\}}\right]'$, and by definition, $\mathbf{RCOV}_t \equiv \mathbf{P}_t + \mathbf{N}_t + \mathbf{M}^+_t + \mathbf{M}^-_t$. If we only consider the market, i.e., the different movements of the index, without further distinguishing between upward and downward states of individual stocks, the original fourfold decomposition can be simplified into a twofold decomposition:

$$\mathbf{MP}_t \equiv \mathbf{P}_t + \mathbf{M}^+_t \equiv \sum_{k=1}^{m} \mathbf{r}^+_{t,k}\mathbf{r}_{t,k}', \quad \mathbf{MN}_t \equiv \mathbf{N}_t + \mathbf{M}^-_t \equiv \sum_{k=1}^{m} \mathbf{r}^-_{t,k}\mathbf{r}'_{t,k}, \quad \mathbf{RCOV}_t \equiv \mathbf{MP}_t + \mathbf{NP}_t$$

To better understand the properties of MP_t and MN_t, assume that the vector log-price process Z_t in model 1 has a constant drift b, unit volatility, no jumps, and a constant correlation coefficient ρ between the stock and the index. This simple model captures the core strength of realized semi-variance estimators in the first-order asymptotic behavior. Under these assumptions and applying the law of large numbers (letting $m \to \infty$), the non-diagonal elements (j,k) of MP_t and MN_t converge in probability to:

$$\text{plim}\, \widehat{MP}^{jk}_t = \text{plim}\, \widehat{MN}^{jk}_t = \psi(\rho) - \psi(-\rho) \tag{2}$$

where $\psi(\rho) = (2\pi)^{-1}\left(\rho \arccos(-\rho) + \sqrt{1-\rho^2}\right)$. Building on BLPQ's research on realized covariance, Bollerslev et al. (2022) decomposes realized beta. Following the definition of four realized semi-betas based on the positive and negative high-frequency returns of stocks and the index by Bollerslev, Li, Patton, & Quaedvlieg (2020b), denoted as BLPQ, they are defined as:

$$\widehat{\beta}_{t,i} \equiv \frac{\sum_{k=1}^{m} r_{t,k,i} f_{t,k}}{\sum_{k=1}^{m} f^2_{t,k}} = \widehat{\beta}^N_{t,i} + \widehat{\beta}^P_{t,i} - \widehat{\beta}^{M+}_{t,i} - \widehat{\beta}^{M-}_{t,i}$$

$$\widehat{\beta}^N_{t,i} = \frac{\sum_{k=1}^{m} r^-_{t,k,i} f^-_{t,k}}{\sum_{k=1}^{m} f^2_{t,k}}, \quad \widehat{\beta}^P_{t,i} = \frac{\sum_{k=1}^{m} r^+_{t,k,i} f^+_{t,k}}{\sum_{k=1}^{m} f^2_{t,k}}, \quad \widehat{\beta}^{M^-}_{t,i} = \frac{-\sum_{k=1}^{m} r^+_{t,k,i} f^-_{t,k}}{\sum_{k=1}^{m} f^2_{t,k}}, \quad \widehat{\beta}^M_{t,i} = \frac{-\sum_{k=1}^{m} r^-_{t,k,i} f^+_{t,k}}{\sum_{k=1}^{m} f^2_{t,k}}$$

where $r_{t,k,i}$, $f_{t,k}$ represent the returns and high-frequency data points of stock i and the index on day t at the k-th data point, and m is the number of high-frequency return data points on day t. Specifically, $f^+_{t,k,i} \equiv \max(f_{t,k,i}, 0)$, $f^-_{t,k,i} \equiv \min(f_{t,k,i}, 0)$, $r^+_{t,k,i} \equiv \max(r_{t,k,i}, 0)$, $r^-_{t,k,i} \equiv \min(r_{t,k,i}, 0)$. Under the same assumptions, the asymptotic theory for realized semi-covariance suggests that the realized semi-beta consistently estimates the true semi-beta:

$$\widehat{\beta}^N_{t,i} \xrightarrow{p} \frac{N_{t,i}}{RV_{t,f}}, \quad \widehat{\beta}^P_{t,i} \xrightarrow{p} \frac{P_{t,i}}{RV_{t,f}}, \quad \widehat{\beta}^{M+}_{t,i} \xrightarrow{p} \frac{-M^+_{t,i}}{RV_{t,f}}, \quad \widehat{\beta}^{M-}_{t,i} \xrightarrow{p} \frac{-M^-_{t,i}}{RV_{t,f}}$$

As mentioned in Section 1, our interest lies in the differences in systematic risk borne by investors in different market return states and whether this difference in volatility can explain differences in cross-sectional stock returns. Therefore, we aggregate the four realized semi-betas based on market return states to obtain the realized semi-betas in market up and market down states:

$$\widehat{\beta}_{t,i}^{MN} = \widehat{\beta}_{t,i}^{N} - \widehat{\beta}_{t,i}^{M-} = \frac{\sum_{k=1}^{m} r_{t,k,i} f_{t,k}^{-}}{\sum_{k=1}^{m} f_{t,k}^{2}}$$

$$\widehat{\beta}_{t,i}^{MP} = \widehat{\beta}_{t,i}^{P} - \widehat{\beta}_{t,i}^{M+} = \frac{\sum_{k=1}^{m} r_{t,k,i} f_{t,k}^{+}}{\sum_{k=1}^{m} f_{t,k}^{2}}$$

$$\widehat{\beta}_{t,i} \equiv \frac{\sum_{k=1}^{m} r_{t,k,i} f_{t,k}}{\sum_{k=1}^{m} f_{t,k}^{2}} = \widehat{\beta}_{t,i}^{MN} + \widehat{\beta}_{t,i}^{MP}$$

As analyzed for MP_t and MN_t earlier, under the same setup, $\widehat{\beta}_{t,i}^{MN}$ and $\widehat{\beta}_{t,i}^{MP}$ converge in probability to:

$$\operatorname{plim} \widehat{\beta}_{t,i}^{MN} = \operatorname{plim} \widehat{\beta}_{t,i}^{MP} = \psi(\rho) - \psi(-\rho)$$

Thus, the difference in realized semi-betas under the same market state can be expressed as:

$$\widehat{\beta}_{t,i}^{abs} = \widehat{\beta}_{t,i}^{MP} - \widehat{\beta}_{t,i}^{MN} = \frac{\sum_{k=1}^{m} r_{t,k,i} |f_{t,k}|}{\sum_{k=1}^{m} f_{t,k}^{2}} \tag{3}$$

Furthermore, based on the convergence in probability results, its long-term mean should theoretically be 0. Therefore, its dispersion can be described by the following formula:

$$\widehat{DS}_{T,i}^{|\beta|} = \frac{1}{T} \sum_{t}^{T} (\widehat{\beta}_{t,i}^{abs} - 0)^2 = \frac{1}{T} \sum_{t}^{T} \left(\frac{\sum_{k=1}^{m} r_{t,k,i} |f_{t,k}|}{\sum_{k=1}^{m} f_{t,k}^{2}} \right)^2 \tag{4}$$

2.2 Intraday Variation of Semi-beta and Corresponding Dispersion

When Bollerslev et al. (2022) conducted pricing studies on four different semi-betas, they first computed four realized semi-betas using high-frequency data. This approach implicitly assumes that beta is a constant value on a given day, a common assumption in previous studies on beta pricing, such as Frazzini & Pedersen (2014) and Bollerslev et al. (2016). However, Andersen et al. (2021), by developing new econometric tools, tested whether there are significant differences in intraday beta, rejecting the null hypothesis of constant intraday beta, indicating that beta is not constant within a day. The existence of this assumption could distort our understanding of the relationship between beta and stock pricing. Therefore, this paper relaxes this assumption and adopts a rolling intraday window to estimate semi-betas and their dispersion in different market up and down states.

Specifically, a rolling window of length k_n is used to calculate the dataset used for estimation. For a given trading day t and sampled data point k, the stock return dataset used for estimation can be represented as:

$$\mathcal{I}_k^m = \{k - k_n + 1, \dots, k\}, \quad \widetilde{\mathcal{I}}_k^m = \{k - k_n + 2, \dots, k\}, \quad k \in [k_n, m].$$

For stock i, the estimate of $\widehat{\beta}_i^{abs}$ on the t-th day and the k-th sampled data point can be expressed as:

$$\widehat{\beta}_{t,k,i}^{abs} = \frac{\sum_{j\in\mathcal{I}_k^m} r_{t,k,i}|f_{t,j}|}{\sum_{j\in\mathcal{I}_k^m} |f_{t,j}|^2} \tag{5}$$

By averaging the values estimated for all sampled data points k within the same day using formula 5, we obtain the estimate of $\widehat{\beta}_i^{abs}$ for that day:

$$\bar{\beta}_{t,i}^{abs} = \frac{1}{m-k+1}\sum_{k}^{m} \widehat{\beta}_{t,k,i}^{abs} = \frac{1}{m-k+1}\sum_{k}^{m} \frac{\sum_{j\in\mathcal{I}_k^m} r_{t,k,i}|f_{t,j}|}{\sum_{j\in\mathcal{I}_k^m} |f_{t,j}|^2} \tag{6}$$

Using formula 5, we can obtain the sequence of $\widehat{\beta}^{abs}$ for stock i on the t-th day. Based on this sequence, we can calculate the dispersion of $\widehat{\beta}^{abs}$ on that day, which is another focus of our subsequent empirical research. To convincingly demonstrate the pricing ability of the dispersion of $\widehat{\beta}^{abs}$ is indeed real, we construct dispersion indicators from three different perspectives: variance, range, and autocorrelation. We then test their pricing abilities separately, and the specific expressions are as follows:

$$\begin{aligned}
\widehat{DS}_{t,i}^{|\beta|} &= \frac{1}{m}\sum_{k}^{m}(\widehat{\beta}_{t,k,i}^{abs} - 0)^2 \\
\widehat{Range}_{t,i}^{|\beta|} &= \sup_{k\in m}(\widehat{\beta}_{t,k,i}^{abs}) - \inf_{k\in m}(\widehat{\beta}_{t,k,i}^{abs}) \\
\widehat{AutoCorr}_{t,i}^{|\beta|} &= -\frac{\sum_{k}^{m-1} \widehat{\beta}_{t,k,i}^{abs}\widehat{\beta}_{t,k+1,i}^{abs}}{\sqrt{\sum_{k}^{m-1} \widehat{\beta}_{t,k,i}^{2,abs}}\sqrt{\sum_{k}^{m-1} \widehat{\beta}_{t,k+1,i}^{2,abs}}}
\end{aligned} \tag{7}$$

To ensure that all three variables reflect increasing dispersion with increasing values, the concept that higher dispersion of $\widehat{\beta}^{abs}$ on that day indicates a higher level of market risk borne by investors, we added a negative sign in front of the traditional autocorrelation coefficient when constructing our $\widehat{AutoCorr}_{t,i}^{|\beta|}$ indicator. In the subsequent empirical analysis, we will focus on examining the differences in systematic risk borne by investors in different market states, as measured by $\bar{\beta}_{t,i}^{abs}$, and their dispersion, as measured by $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$, to see if they can significantly explain differences in cross-sectional stock returns in the short term.

3 Data and variable

In this section, we will first explore the high-frequency data used in the empirical analysis, introduce the control variables in portfolio sorting and cross-sectional pricing regression, and present some descriptive statistical results.

3.1 Data

Our empirical analysis relies on high-frequency intraday trading data obtained from the RESSET database, including securities listed on the Shanghai Stock Exchange (SSE) Main Board and STAR Market, as well as those listed on the Shenzhen Stock Exchange (SZSE) Main Board and ChiNext Board. The sample period spans from April 2005 to December 2022. During the data cleaning process, we follow the procedure outlined in Liu et al. (2019), excluding stock data for the month with less than two-thirds of the statutory trading days, stocks with an ST label, stocks with less than 6 months of listing history, and data with abnormal returns on the resumption day (exceeding the daily price limit).

Additionally, we use daily stock return, outstanding shares, total market capitalization, and other low-frequency data from the CSMAR database. We select the one-year benchmark deposit interest rate as a proxy for the risk-free rate. Given that Liu et al. (2019) provides factor returns data for the CH3 multi-factor model until 2021[1], we autonomously construct daily CH3 multi-factor model returns following their provided construction process as the benchmark pricing model. The correlation matrix of factor returns between our constructed model and Liu et al. (2019) in the same trading intervals is presented in Table 1, where uppercase letters represent factors provided by Liu et al. (2019), and lowercase letters denote factors constructed by us, with correlations consistently exceeding 90%.

3.2 Other controls variables

Past empirical studies have attempted to link cross-sectional variations in stock returns to other explanatory variables and firm characteristics. In order to eliminate the influence of other

[1] Source of data on factor yields: https://finance.wharton.upenn.edu/ stambaug/

Table 1: Matrix of correlation coefficients of corresponding factor returns

	MKT	SMB	VMG
mkt	0.9981	0.1877	-0.1886
smb	0.1739	0.9560	-0.4660
vmg	-0.2179	-0.5591	0.9103

variables on the pricing ability of Semi-beta differences and their dispersion in subsequent portfolio sorting and cross-sectional regressions, we explicitly define the following control variables:

- Realized Beta (beta): Observed beta value of the stock.
- Down-side Semi-beta (Down-side beta): Semi-beta value of the stock in market downturns.
- Jump Beta (Discon beta): Jump beta value of the stock.
- Company Size (ME): Market capitalization of the company.
- Momentum (MOM): Momentum of the stock.
- Reversal (REV): Reversal of the stock.
- Idiosyncratic Volatility (IVOL): Idiosyncratic volatility of the stock.
- Weekly Maximum Daily Return (MAX): Maximum daily return of the stock each week.
- Weekly Minimum Daily Return (MIN): Minimum daily return of the stock each week.
- Illiquidity (ILLIQ): Illiquidity of the stock.
- Relative Sign Jump (RSJ): Relative sign jump.

These control variables are constructed following standard procedures outlined in the literature. The specific construction process is detailed in Appendix A.

3.3 Estimation results

When estimating $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, $\widehat{AutoCorr}^{|\beta|}_{t,i}$, and other high-frequency factors, we resample the 1-minute high-frequency trading data obtained from the RESSET database into 5-minute trading data. This is done to avoid biases caused by market microstructure effects in "overly fine" sampling (Hansen & Lunde (2006) and Andersen et al. (2001)). Since normal trading hours in the A-share market are from 09:30 to 11:30 and 13:00 to 15:00 for a total of 4 hours, we obtain 48 observations each day, serving as the benchmark data for subsequent estimations.

Furthermore, to enhance estimation accuracy, if the missing trading data for stock i on day t exceeds one-fourth of the theoretical sampling quantity (48), we exclude the data for that stock on that day from the dataset. For days with missing data that do not meet the exclusion criteria, we use the common practice of forward-filling. During estimation, the rolling estimation window k_n is set to 25, which equals 2 hours and 5 minutes. Due to the unique limit-up/limit-down system in the A-share market, estimating stocks that are one-way limit up (down) or rapidly hit the limit up (down) and maintain that status for the entire day may lead to substantial bias. For robustness, if the number of non-zero returns for a stock on a given day is less than two-thirds of the theoretical sampling quantity, we exclude that stock's data for that day.

Applying these rules and referring to the methodology in Section 2 for metric estimation, we aggregate all focus variables and control variables by taking weekly averages. The choice of a weekly frequency, as opposed to the monthly frequency commonly used in asset pricing studies, is due to the core focus of this paper on whether the differences in semi-beta in different market return states and its dispersion have pricing ability or not. Given that intraday semi-beta itself is short-term and rapidly changing, an excessively long rebalancing period would result in significant information loss. This choice aligns with Bollerslev et al. (2022), who also focused on the pricing ability of RV-based Relative Sign Jump (RSJ) at the intraday frequency.

Now let's turn our attention to the actual estimation results. Panel A in Table 2 provides the cross-sectional averages, medians, and standard deviations of $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, $\widehat{AutoCorr}^{|\beta|}_{t,i}$, and other control variables after aggregating to the weekly level, with ME and ILLIQ scaled for better presentation[2]. The mean of realized beta is close to 1, aligning with our economic intuition. Additionally, the mean of $\bar{\beta}^{abs}_{t,i}$ is close to 0, consistent with the theoretical results obtained earlier. Panel B reports the cross-sectional correlations of the corresponding variables. The correlation between $\bar{\beta}^{abs}_{t,i}$ and RSJ, as well as REV, is quite high, exceeding 40%. For RSJ, this is not particularly surprising, as RSJ is also obtained by subtracting positive and negative decompositions of risk indicators. For REV, it may indicate the presence of negative pricing ability of $\bar{\beta}^{abs}_{t,i}$ similar to REV types. Furthermore, the correlation between $\widehat{DS}^{|\beta|}_{t,i}$ and $\widehat{Range}^{|\beta|}_{t,i}$ is high, exceeding 70%, while the correlations between the first two and $\widehat{AutoCorr}^{|\beta|}_{t,i}$ are negative, indicating that, although all three are indicators reflecting the degree of dispersion, there are obvious differences in the information they capture.

Figure 1 displays the unconditional distribution of $\bar{\beta}^{abs}_{t,i}$ (Beta_abs_intra), $\widehat{DS}^{|\beta|}_{t,i}$ (Square),

[2] ME scaled down by 1000 times, ILLIQ scaled up by 1000000 times

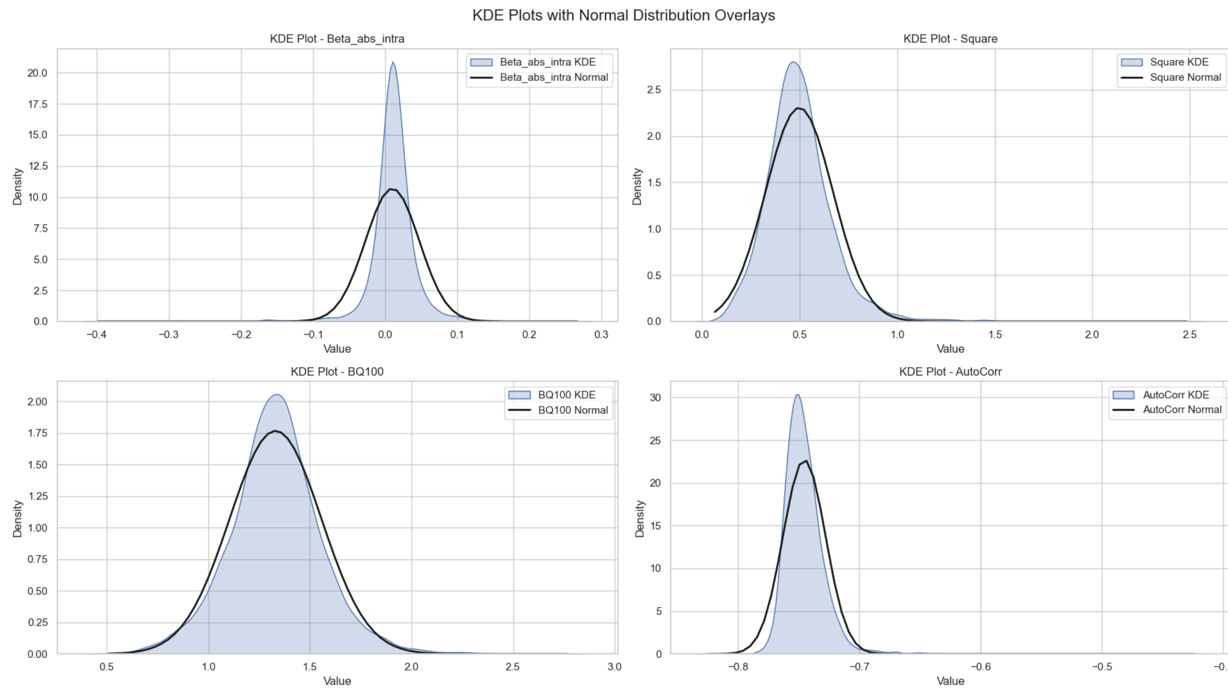

Figure 1: Kernel density estimates of the unconditional distributions

$\widehat{Range}_{t,i}^{|\beta|}$ (BQ100), and $\widehat{AutoCorr}_{t,i}^{|\beta|}$ (AutoCorr) on the cross-section through kernel density estimation. The light blue shaded area represents the actual kernel density estimation distribution of the variable, and the corresponding black solid line shows the normal distribution results for a distribution with the same mean and standard deviation. It can be observed that all four factors have significant peaks in their distributions, especially pronounced for $\bar{\beta}_{t,i}^{abs}$. Moreover, compared to a normal distribution, there is no particularly noticeable left or right skewness.

4 Portfolio sorts

In this section, we begin the empirical study of whether the differences and dispersion in two types of semi-beta under different market return states can explain cross-sectional variations in stock returns. We examine whether portfolios constructed based on $\bar{\beta}_{t,i}^{abs}$, $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$ under different sorting schemes can generate significant excess returns. To do this, we consider univariate sorting predictive portfolios and simultaneously design bivariate sorting predictive portfolios to control for other risk factors and firm characteristics. Similar to Bollerslev et al. (2016), we will focus primarily on the pricing ability of different factors under the equal-weighted construction method.

Specifically, at the end of each Friday, we first sort all stocks from smallest to largest based

Table 2: Descriptive Statistic

	$\bar{\beta}^{abs}$	$\widehat{Range}^{\lvert\beta\rvert}$	$\widehat{AutoCorr}^{\lvert\beta\rvert}$	$\widehat{DS}^{\lvert\beta\rvert}$	beta	BM	ME	MOM	ILLIQ	IVOL	CSK	CKT	RSJ	disconBeta	Beta_neg	MAX	MIN	REV
Panel A. Cross-Sectional Summary Statistics																		
mean	0.01	1.3311	-0.7454	0.4985	0.8987	0.4199	14127778.7	0.0801	0.0005	0.0201	-0.1229	0.4464	0.0678	1.6369	0.4355	0.0282	-0.028	-0.001
std	0.0374	0.2257	0.0176	0.173	0.2249	0.4458	48162124.32	0.1912	0.0004	0.0043	0.1366	0.1901	0.0279	0.2701	0.1078	0.0064	0.0055	0.0073
50%	0.0112	1.3292	-0.748	0.483	0.9119	0.364	5624780.015	0.045	0.0004	0.0199	-0.1162	0.4549	0.0718	1.613	0.4435	0.0281	-0.028	0
Panel B. Cross-Sectional Correlations																		
$\bar{\beta}^{abs}$	1	0.1509	-0.043	0.255	0.061	0.0077	0.0185	0.0045	-0.0388	0.0202	0.0111	-0.0183	0.4262	0.0136	-0.2805	0.3266	0.2366	0.4076
$\widehat{Range}^{\lvert\beta\rvert}$		1	-0.2316	0.7162	0.5177	-0.0736	-0.0622	-0.0961	-0.1309	0.5021	0.233	-0.1294	0.1877	0.4031	0.3839	0.3882	-0.2192	0.1573
$\widehat{AutoCorr}^{\lvert\beta\rvert}$			1	-0.1209	-0.0575	-0.0068	-0.0145	0.006	0.0536	0.0164	0.0059	-0.0152	-0.0029	-0.0054	-0.0378	-0.0168	0.0116	-0.0056
$\widehat{DS}^{\lvert\beta\rvert}$				1	0.3949	-0.0428	-0.0344	-0.0595	-0.0781	0.365	0.1536	-0.0883	0.1498	0.2837	0.264	0.3538	-0.1884	0.1457
beta					1	0.0033	0.0223	-0.035	-0.2578	0.2616	0.1095	-0.048	0.0584	0.3794	0.8634	0.2044	-0.2084	0.0238
BM						1	0.0608	0.0821	-0.0413	-0.1319	0.0124	0.029	-0.0062	-0.1291	0.0015	-0.0811	0.1011	0.0035
ME							1	-0.0409	-0.1751	-0.0755	0.0185	0.0331	-0.0103	-0.0836	0.0088	-0.0202	0.0445	0.0074
MOM								1	0.1228	-0.1775	-0.0395	0.0066	0.0016	-0.1897	-0.0301	-0.092	0.0873	-0.0095
ILLIQ									1	-0.1599	-0.118	0.0184	-0.0684	-0.1102	-0.2119	-0.0481	-0.0212	-0.029
IVOL										1	0.3618	-0.2081	0.0506	0.4272	0.2257	0.2811	-0.3257	-0.0203
CSK											1	-0.1477	0.0389	0.0585	0.0864	0.1365	-0.0989	0.0312
CKT												1	-0.0566	-0.0743	-0.0314	-0.074	0.025	-0.0339
RSJ													1	0.0342	-0.2518	0.451	0.3627	0.6186
disconBeta														1	0.3393	0.1872	-0.2448	-0.0233
Beta_neg															1	-0.0104	-0.3365	-0.2281
MAX																1	-0.0401	0.6372
MIN																	1	0.504
REV																		1

on the corresponding indicators and divide them into five groups. Then, we construct portfolios by weighting all stocks within each group and calculate the subsequent week's portfolio returns. To investigate whether these return differences are due to exposure to systematic risk, we regress the excess returns of each portfolio and the HML portfolio on the three factors (Market factor MKT, Size factor SMB, Value factor VMG) to calculate the alpha of the CH3 multi-factor model, i.e., the regression intercept. In the table, the AvgRet and Alpha columns respectively show the weighted returns of the corresponding portfolios and the time-series mean and alpha of the risk-adjusted excess returns based on the CH3 factor model proposed by Liu et al. (2019). In addition, the HML row reports the return difference between the highest group (G5) and the lowest group (G1) portfolios, along with the corresponding Newey-West robust t-statistic and the associated p-value.

4.1 Single-Sorted Portfolios

Table 3: Predictive Single-Sorted Portfolios

Single Sorted								
	AvgRet	Alpha	AvgRet	Alpha	AvgRet	Alpha	AvgRet	Alpha
	$\bar{\beta}^{abs}_{t,i}$		$\widehat{DS}^{\|\beta\|}_{t,i}$		$\widehat{Range}^{\|\beta\|}_{t,i}$		$\widehat{AutoCorr}^{\|\beta\|}_{t,i}$	
G01	0.2162	-0.1507	0.2719	-0.0588	0.3179	-0.0201	0.1899	-0.1798
G02	0.2712	-0.1054	0.2563	-0.1068	0.3008	-0.0623	0.1759	-0.2041
G03	0.2358	-0.1391	0.2405	-0.1323	0.2498	-0.1274	0.169	-0.2087
G04	0.1757	-0.197	0.163	-0.2279	0.1347	-0.2492	0.1626	-0.2105
G05	-0.1039	-0.4687	-0.1366	-0.5349	-0.2081	-0.6018	0.0976	-0.2579
HML	-0.3201	-0.318	-0.4084	-0.4762	-0.526	-0.5816	-0.0922	-0.0781
t	-8.7767	-8.7442	-7.7539	-8.8424	-9.3549	-9.9708	-4.3299	-3.4475
p	0	0	0	0	0	0	0	0.0006
	beta		Down-side beta		RSJ		REV	
G01	0.2353	-0.0785	0.1725	-0.1403	0.3267	-0.0396	0.3299	-0.0441
G02	0.2464	-0.102	0.2219	-0.135	0.3312	-0.0405	0.3873	0.0238
G03	0.2077	-0.1634	0.2156	-0.1554	0.2736	-0.1066	0.29	-0.0745
G04	0.1506	-0.241	0.1663	-0.2271	0.1078	-0.2713	0.1092	-0.2672
G05	-0.0449	-0.4758	0.0189	-0.403	-0.2443	-0.6029	-0.3214	-0.6986
HML	-0.2802	-0.3973	-0.1535	-0.2627	-0.571	-0.5633	-0.6513	-0.6545
t	-4.8172	-7.11	-2.8223	-4.971	-11.9889	-12.0538	-9.9481	-10.6722
p	0	0	0.0049	0	0	0	0	0

In Table 3, we present the univariate sorting results for eight key factors. These factors include the four semi-beta factors we propose, as well as four control variables that may be highly correlated with these factors. We focus on $\bar{\beta}_{t,i}^{abs}$, $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$.

For $\bar{\beta}_{t,i}^{abs}$, we observe significant negative pricing ability, indicating that higher values of $\widehat{\beta}_{t,i}^{MN}$ relative to $\widehat{\beta}_{t,i}^{MP}$ are associated with higher returns in the following week. The weekly HML return is about -32 basis points, and the alpha values adjusted by the CH3 multi-factor model exhibit a similar trend, with robust t-statistics of -8.78 and -8.74, respectively. In contrast, Down-side beta, the semi-beta when the market return is negative, although also showing significant pricing ability, has a slightly weaker pricing strength compared to $\bar{\beta}_{t,i}^{abs}$. The HML return is less than half of $\bar{\beta}_{t,i}^{abs}$, and the significance drops significantly, indicating that it is not only the Down-side semi-beta but the difference between Up-side and Down-side semi-beta that is a more important source of risk and pricing.

For $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$, they all exhibit consistent negative pricing ability. This implies that the differences in market risk borne by stocks under different market states have a significant pricing effect. More importantly, the smaller, i.e., more stable, the dispersion of these differences, the higher the returns of stocks in the next week. Among them, $\widehat{DS}_{t,i}^{|\beta|}$ and $\widehat{Range}_{t,i}^{|\beta|}$ have higher HML returns, at -40 and -53 basis points per week, respectively, while $\widehat{AutoCorr}_{t,i}^{|\beta|}$ has a slightly lower HML return, at -9 basis points per week, showing the same characteristics of significance. The three different measures of dispersion show consistent and significant pricing ability, demonstrating the reliability and robustness of the results. Additionally, beta, RSJ, and REV also exhibit significant negative pricing ability. In the next section of bivariate sorting, we will further examine whether the pricing ability of $\bar{\beta}_{t,i}^{abs}$, $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$ disappears after controlling for these factors with significant pricing ability.

4.2 Double-Sorted Portfolios

Our univariate portfolio sorting results indicate that the differences and dispersion of semi-beta under different market conditions have significant pricing ability, and the resulting high returns remain significant even after risk adjustment through factor models. However, univariate sorting does not explicitly control for the pricing effects of other factors. As shown in the descriptive statistics in Table 2, these four factors exhibit high correlations with specific control variables. Therefore, to more directly identify the sources of risk premiums for different factors, we employ a series of bivariate sorts to control for other commonly observed factors in the literature, expanding the research from univariate sorting.

To implement bivariate sorting, we follow the method of Bollerslev et al. (2016). First, we divide all stocks into 5 groups based on different control variables for each week. Then, within each group, we further divide the stocks into 5 new groups based on the differences in $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, and $\widehat{AutoCorr}^{|\beta|}_{t,i}$. This process results in 5x5=25 portfolios. For each of the five different control variable portfolios, we average the returns of the five core portfolios to generate portfolios that exhibit significant cross-portfolio changes in core variables but minimal changes in control variables. This approach allows us to observe the pricing ability of $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, and $\widehat{AutoCorr}^{|\beta|}_{t,i}$ while controlling for specific factors.

Tables 4 and 5 present the bivariate sorting results for $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, and $\widehat{AutoCorr}^{|\beta|}_{t,i}$. For $\bar{\beta}^{abs}_{t,i}$, regardless of the controlled variable, both HML returns and risk-adjusted alpha returns are significant at the 1% level. When controlling for RSJ and REV, the pricing effect slightly diminishes, with absolute returns dropping from around -30 basis points per week to around -10 basis points, and absolute t-values decreasing from around 9 to around 3. This result aligns with the high correlation between $\bar{\beta}^{abs}_{t,i}$ and RSJ and REV, as shown in the descriptive statistics in Table 2. The moderate decrease in pricing ability with RSJ controlling is expected since both RSJ and $\bar{\beta}^{abs}_{t,i}$ capture risk differences under different market conditions. REV represents a short-term reversal effect, and its ability to dampen the pricing ability of $\bar{\beta}^{abs}_{t,i}$ can be explained by the nature of how REV is constructed. However, it is crucial to emphasize that, although RSJ and REV partially explain the risk premium of $\bar{\beta}^{abs}_{t,i}$, both HML returns and alpha returns of $\bar{\beta}^{abs}_{t,i}$ maintain economic and statistical significance, indicating unique information not covered by the former two.

Now, turning our attention to the measures of dispersion, as shown in Tables 4b and 5a, $\widehat{DS}^{|\beta|}_{t,i}$ and $\widehat{Range}^{|\beta|}_{t,i}$ maintain HML and alpha returns at 1% significance level, irrespective of the controlled variable. The absolute values of HML and alpha returns remain stable in the range of 30-60 basis points per week, with absolute t-values not falling below 7. Regarding the measure of dispersion based on autocorrelation coefficients, $\widehat{AutoCorr}^{|\beta|}_{t,i}$, as shown in Table 5b, despite having smaller absolute values in terms of HML and alpha returns and robust t-statistics, ranging around 9 basis points and 4, respectively, it also exhibits a high degree of stability, demonstrating robust pricing ability for the differences in semi-beta dispersion under different market return states.

To further examine the pricing relationships between $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, $\widehat{AutoCorr}^{|\beta|}_{t,i}$, and our key control variables, Table 6 presents bivariate sorting details when controlling for realized beta and RSJ. Panel A displays the bivariate sorting results controlling for realized beta. For our four core variables of interest, regardless of the value of realized beta or the group it belongs to, the results remain significant at the 1% level. The only exception is when grouping by $\widehat{AutoCorr}^{|\beta|}_{t,i}$ after controlling for the minimum realized beta, where HML returns are no longer significant in this specific case. Panel B presents the bivariate sorting details controlling for the relative sign

Table 4: Predictive double-sorted aggregation result-I

	BM	ME	MOM	REV	IVOL	ILLIQ	MAX	MIN	CSK	CKT	RSJ	beta	Down-side beta	Discon beta
G01	0.2239	0.2213	0.2215	0.1268	0.2372	0.2158	0.1916	0.2002	0.2255	0.2172	0.1347	0.2193	0.2454	0.2201
G02	0.27	0.2733	0.2699	0.2157	0.2661	0.2653	0.2259	0.2525	0.26	0.2669	0.2236	0.2636	0.2727	0.2732
G03	0.2365	0.2342	0.2378	0.2106	0.2113	0.2295	0.2091	0.23	0.2386	0.2397	0.2176	0.2361	0.2392	0.2295
G04	0.18	0.1689	0.1717	0.1935	0.1407	0.1775	0.1652	0.1719	0.1678	0.1644	0.1946	0.1598	0.1572	0.1637
G05	-0.1143	-0.1019	-0.1047	0.0494	-0.0595	-0.0921	0.0035	-0.059	-0.0957	-0.0922	0.0256	-0.0829	-0.1183	-0.0904
HML	-0.3381***	-0.3232***	-0.3262***	-0.0774***	-0.2967***	-0.3079***	-0.1881***	-0.2592***	-0.3212***	-0.3094***	-0.1091***	-0.3022***	-0.3638***	-0.3104***
t	-9.6594	-9.3468	-9.2709	-2.9599	-8.6738	-8.7982	-6.0633	-8.1912	-9.2277	-8.7781	-3.6286	-8.8176	-10.0788	-9.0388
Alpha	-0.3373***	-0.316***	-0.3238***	-0.0815***	-0.2956***	-0.2992***	-0.178***	-0.2698***	-0.3163***	-0.308***	-0.1125***	-0.2955***	-0.3856***	-0.3078***
Alpha_t	-9.6224	-8.9118	-9.2633	-3.0235	-8.6844	-8.3737	-5.5969	-8.6182	-9.108	-8.744	-3.6523	-8.7357	-10.7417	-9.0182

(a) $\bar{\beta}_{t,i}^{abs}$

	BM	ME	MOM	REV	IVOL	ILLIQ	MAX	MIN	CSK	CKT	RSJ	beta	Down-side beta	Discon beta
G01	0.2766	0.2832	0.2846	0.2366	0.194	0.2641	0.2094	0.2876	0.2788	0.2746	0.2483	0.2022	0.2229	0.2213
G02	0.2562	0.2524	0.2622	0.2332	0.203	0.2384	0.2189	0.2768	0.2545	0.2586	0.2329	0.2313	0.2584	0.2236
G03	0.249	0.2346	0.2304	0.215	0.1987	0.2374	0.2107	0.2195	0.2298	0.2231	0.2251	0.2262	0.2351	0.2383
G04	0.1573	0.1611	0.1596	0.1748	0.1905	0.1576	0.1658	0.1553	0.1483	0.1656	0.1596	0.2008	0.1952	0.1835
G05	-0.1436	-0.136	-0.1412	-0.0636	0.0093	-0.1019	-0.0092	-0.1437	-0.1158	-0.1259	-0.0702	-0.0645	-0.1155	-0.0711
HML	-0.4201***	-0.4192***	-0.4257***	-0.3002***	-0.1846***	-0.3661***	-0.2186***	-0.4312***	-0.3947***	-0.4005***	-0.3186***	-0.2667***	-0.3384***	-0.2924***
t	-8.6338	-8.4704	-8.8517	-6.0506	-4.6547	-7.2412	-5.016	-9.5347	-7.8979	-8.1497	-6.2601	-5.6925	-7.4084	-7.1963
Alpha	-0.4881***	-0.4802***	-0.4803***	-0.3587***	-0.2434***	-0.419***	-0.2795***	-0.484***	-0.4571***	-0.4692***	-0.3871***	-0.2741***	-0.364***	-0.3298***
Alpha_t	-9.4512	-9.5735	-9.8337	-7.6424	-5.886	-8.1081	-6.4421	-10.6131	-9.0782	-9.4535	-7.6998	-5.6022	-7.7038	-7.5537

(b) $\widehat{DS}_{t,i}^{|\beta|}$

Table 5: Predictive double-sorted aggregation result-II

	BM	ME	MOM	REV	IVOL	ILLIQ	MAX	MIN	CSK	CKT	RSJ	beta	Down-side beta	Discon beta
G01	0.3136	0.3318	0.3236	0.2746	0.2407	0.3043	0.2648	0.3379	0.3276	0.3209	0.2825	0.2572	0.2816	0.2723
G02	0.3009	0.3003	0.3048	0.2695	0.2277	0.2838	0.2601	0.2879	0.2898	0.2951	0.2684	0.2555	0.2756	0.2651
G03	0.2606	0.2412	0.239	0.2267	0.2076	0.2349	0.2164	0.2317	0.2367	0.2365	0.2302	0.2529	0.2669	0.2334
G04	0.1356	0.1338	0.1438	0.1453	0.1646	0.1338	0.1358	0.1379	0.1203	0.1315	0.1391	0.1753	0.1629	0.1705
G05	-0.2148	-0.2119	-0.2153	-0.1204	-0.0451	-0.1613	-0.0816	-0.2	-0.1787	-0.1883	-0.1244	-0.1449	-0.1909	-0.1455
HML	-0.5284***	-0.5437***	-0.5389***	-0.395***	-0.2857***	-0.4656***	-0.3464***	-0.5379***	-0.5063***	-0.5091***	-0.4069***	-0.4021***	-0.4725***	-0.4177***
t	-10.3298	-10.2541	-10.6276	-7.6878	-7.0054	-8.6773	-7.4551	-10.6075	-9.749	-9.7577	-7.6142	-8.3928	-9.7833	-9.3232
Alpha	-0.5832***	-0.5941***	-0.579***	-0.4489***	-0.3286***	-0.4988***	-0.3909***	-0.5847***	-0.5582***	-0.5621***	-0.4662***	-0.3873***	-0.4799***	-0.4431***
Alpha_t	-10.589	-10.9131	-10.9733	-9.2285	-7.6647	-9.0073	-8.3788	-11.4932	-10.5594	-10.7768	-8.6441	-7.9373	-9.7407	-9.2331

(a) $\widehat{Range}_{t,i}^{|\beta|}$

	BM	ME	MOM	REV	IVOL	ILLIQ	MAX	MIN	CSK	CKT	RSJ	beta	Down-side beta	Discon beta
G01	0.1851	0.1901	0.1854	0.1973	0.1864	0.1958	0.1915	0.1967	0.1892	0.1865	0.1949	0.1824	0.183	0.1808
G02	0.1789	0.1815	0.1763	0.1679	0.1651	0.1873	0.1713	0.1708	0.1699	0.1761	0.1743	0.1808	0.1811	0.1795
G03	0.1728	0.1669	0.1682	0.1682	0.1789	0.1634	0.1718	0.1669	0.171	0.1686	0.1617	0.1753	0.1728	0.1772
G04	0.1568	0.1556	0.1597	0.1535	0.1601	0.1608	0.1602	0.153	0.1593	0.163	0.1549	0.1667	0.1667	0.1632
G05	0.1013	0.1005	0.1054	0.1082	0.1046	0.0875	0.1001	0.1074	0.1056	0.1007	0.1093	0.0901	0.0917	0.0945
HML	-0.0838***	-0.0896***	-0.08***	-0.0891***	-0.0818***	-0.1083***	-0.0914***	-0.0893***	-0.0836***	-0.0859***	-0.0855***	-0.0923***	-0.0913***	-0.0862***
t	-4.1401	-4.3288	-3.8433	-4.4247	-4.0548	-5.0831	-4.5983	-4.3096	-4.2105	-4.1022	-4.2411	-4.5144	-4.526	-4.1954
Alpha	-0.0692***	-0.0823***	-0.0672***	-0.0775***	-0.0676***	-0.1013***	-0.0778***	-0.0746***	-0.0718***	-0.0732***	-0.0707***	-0.0844***	-0.0831***	-0.0716***
Alpha_t	-3.2138	-3.7372	-3.0475	-3.6457	-3.1768	-4.4599	-3.6459	-3.3928	-3.3903	-3.3057	-3.2948	-3.9732	-3.8801	-3.3155

(b) $\widehat{AutoCorr}_{t,i}^{|\beta|}$

Table 6: Predictive double-sorted details

	beta_G01	beta_G02	beta_G03	beta_G04	beta_G05	AvgRet	Alpha	RSJ_G01	RSJ_G02	RSJ_G03	RSJ_G04	RSJ_G05	AvgRet	Alpha
	Panel A Control realized beta							Panel B Control RSJ						
				$\bar{\beta}_{t,i}^{abs}$							$\bar{\beta}_{t,i}^{abs}$			
G01	0.2569	0.3198	0.2458	0.2271	0.0469	0.2193	-0.1463	0.2157	0.3185	0.2613	0.0905	-0.2127	0.1347	-0.2288
G02	0.3332	0.347	0.299	0.2527	0.0862	0.2636	-0.1148	0.3935	0.3444	0.3252	0.1977	-0.143	0.2236	-0.1535
G03	0.3283	0.2979	0.271	0.2245	0.0585	0.2361	-0.1433	0.3809	0.3776	0.3294	0.1501	-0.1497	0.2176	-0.1585
G04	0.2617	0.2427	0.2152	0.1561	-0.0765	0.1598	-0.2139	0.3637	0.3709	0.3027	0.125	-0.1893	0.1946	-0.1778
G05	-0.0025	0.0251	0.0087	-0.1069	-0.3389	-0.0829	-0.4418	0.2807	0.2448	0.1504	-0.0227	-0.5252	0.0256	-0.3413
HML	-0.2595	-0.2948	-0.2371	-0.334	-0.3858	-0.3022	-0.2955	0.065	-0.0737	-0.1109	-0.1132	-0.3125	-0.1091	-0.1125
t	-6.5632	-7.4685	-6.0335	-6.8437	-7.4023	-8.8176	-8.7357	1.3737	-1.9136	-2.5142	-2.7952	-6.9341	-3.6286	-3.6523
p	0	0	0	0	0	0	0	0.1699	0.056	0.0121	0.0053	0	0.0003	0.0003
				$\widehat{DS}_{t,i}^{\lvert\beta\rvert}$							$\widehat{DS}_{t,i}^{\lvert\beta\rvert}$			
G01	0.2923	0.2656	0.2178	0.18	0.0553	0.2022	-0.1609	0.3426	0.3621	0.32	0.2028	0.0143	0.2483	-0.0812
G02	0.3225	0.2964	0.2551	0.2181	0.0644	0.2313	-0.1405	0.3452	0.3486	0.3385	0.1978	-0.0654	0.2329	-0.132
G03	0.3387	0.2966	0.2671	0.205	0.0236	0.2262	-0.1498	0.4015	0.3594	0.3402	0.1938	-0.1693	0.2251	-0.1473
G04	0.2876	0.2891	0.244	0.2103	-0.0271	0.2008	-0.1738	0.3698	0.3417	0.2862	0.0967	-0.2965	0.1596	-0.2318
G05	-0.0632	0.0851	0.0555	-0.0597	-0.3401	-0.0645	-0.435	0.1752	0.2439	0.0841	-0.151	-0.7034	-0.0702	-0.4683
HML	-0.3555	-0.1805	-0.1624	-0.2397	-0.3954	-0.2667	-0.2741	-0.1674	-0.1181	-0.2359	-0.3538	-0.7177	-0.3186	-0.3871
t	-5.9213	-3.344	-2.9853	-4.681	-6.1634	-5.6925	-5.6022	-2.9752	-2.0256	-3.7856	-6.0831	-10.3368	-6.2601	-7.6998
p	0	0.0009	0.0029	0	0	0	0	0.003	0.0431	0.0002	0	0	0	0
				$\widehat{Range}_{t,i}^{\lvert\beta\rvert}$							$\widehat{Range}_{t,i}^{\lvert\beta\rvert}$			
G01	0.3111	0.306	0.2725	0.2622	0.1341	0.2572	-0.1195	0.3507	0.3641	0.3719	0.2221	0.1036	0.2825	-0.0526
G02	0.3502	0.2929	0.2982	0.2452	0.0907	0.2555	-0.1222	0.3995	0.4	0.3706	0.2253	-0.0533	0.2684	-0.0953
G03	0.3411	0.3365	0.3025	0.2173	0.0673	0.2529	-0.1144	0.4152	0.3617	0.3345	0.1998	-0.1601	0.2302	-0.1461
G04	0.2932	0.2711	0.2334	0.1526	-0.0736	0.1753	-0.1969	0.335	0.3487	0.2396	0.0998	-0.3276	0.1391	-0.2475
G05	-0.1176	0.0259	-0.0663	-0.1239	-0.4426	-0.1449	-0.5069	0.1346	0.182	0.0516	-0.207	-0.7833	-0.1244	-0.5189
HML	-0.4287	-0.2801	-0.3388	-0.3861	-0.5767	-0.4021	-0.3873	-0.2161	-0.182	-0.3203	-0.429	-0.8869	-0.4069	-0.4662
t	-6.7955	-5.2506	-6.2841	-7.5228	-8.1037	-8.3928	-7.9373	-3.685	-3.0429	-5.2253	-6.5342	-12.2581	-7.6142	-8.6441
p	0	0	0	0	0	0	0	0.0002	0.0024	0	0	0	0	0
				$\widehat{AutoCorr}_{t,i}^{\lvert\beta\rvert}$							$\widehat{AutoCorr}_{t,i}^{\lvert\beta\rvert}$			
G01	0.2194	0.267	0.2409	0.1832	0.0015	0.1824	-0.1865	0.3433	0.3361	0.3297	0.1352	-0.1702	0.1949	-0.1749
G02	0.2449	0.2691	0.2046	0.1505	0.0349	0.1808	-0.2	0.3685	0.3657	0.2836	0.0755	-0.2221	0.1743	-0.2067
G03	0.2219	0.2734	0.2546	0.1805	-0.0538	0.1753	-0.1972	0.3474	0.3304	0.267	0.1214	-0.2577	0.1617	-0.2137
G04	0.2524	0.2408	0.2173	0.1544	-0.0315	0.1667	-0.2062	0.3165	0.3608	0.2561	0.1283	-0.2871	0.1549	-0.2202
G05	0.2383	0.1817	0.1217	0.0843	-0.1755	0.0901	-0.2709	0.2579	0.2637	0.2316	0.0785	-0.285	0.1093	-0.2456
HML	0.019	-0.0853	-0.1192	-0.099	-0.177	-0.0923	-0.0844	-0.0854	-0.0724	-0.0981	-0.0567	-0.1149	-0.0855	-0.0707
t	0.7123	-2.7902	-3.8788	-2.6927	-4.0529	-4.5144	-3.9732	-2.4353	-2.3672	-2.9593	-1.6942	-3.1883	-4.2411	-3.2948
p	0.4765	0.0054	0.0001	0.0072	0.0001	0	0.0001	0.0151	0.0181	0.0032	0.0906	0.0015	0	0.001

jump RSJ. Consistent with the results showing a decline in $\bar{\beta}^{abs}_{t,i}$ after controlling for RSJ in Table 4a, when controlling for the minimum RSJ in the first two groups, HML returns of $\bar{\beta}^{abs}_{t,i}$ are no longer significant, indicating a loss of pricing ability. A similar situation occurs in the sorting results of $\widehat{AutoCorr}^{|\beta|}_{t,i}$ when controlling for the second smallest RSJ group. However, for $\widehat{DS}^{|\beta|}_{t,i}$ and $\widehat{Range}^{|\beta|}_{t,i}$, their HML and alpha returns remain significant at the 1% level, regardless of the control measures.

5 Cross-sectional pricing regressions

In the portfolio sorting methods discussed in the previous section, no strong assumptions were imposed on the model. However, the approach of sorting stocks and aggregating them into portfolios overlooks potentially important cross-sectional information at the company level. Additionally, while double-sorted portfolios can control for other variables, it can only control one variable at a time, making it impossible to assess the pricing ability of core variables when simultaneously controlling for multiple variables. Therefore, we turn to the cross-sectional regression method based on company-level data proposed by Fama & MacBeth (1973).

This method allows for the simultaneous estimation of risk premiums for different factors while controlling for multiple variables. For simplicity, let's assume the unit time interval is one week, so every week is denoted as $t = 1, 2, ..., T$, and for a specific weekly period t, all available samples are represented as $i = 1, 2, ..., N_t$. The cross-sectional pricing regression for stock i in week t can be expressed as:

$$r_{i,t+1} - rf_{t+1} = \gamma_{0,t} + \sum_{j=1}^{\kappa} \gamma_{j,t} Z_{j,i,t} + \epsilon_{i,t+1}, \quad i = 1, 2, \ldots, N,$$

where $r_{i,t+1}$ and rf_{t+1} represent the cumulative return of stock i in week $t+1$ and the risk-free rate, respectively. The K stock-specific control variables $Z_{j,i,t}$ are measured at the end of week t. After estimating the slope coefficients $\gamma_{j,t}$ for each week, i.e., the risk premiums for corresponding factors, we compute the time-series mean of the estimated values $\hat{\gamma}_{j,t}$ to assess whether different variables can significantly predict future returns. Since the units of different variables are not consistent, we standardize the variables by taking Z-scores before regression on the cross-section. To prevent extreme values from severely biasing the regression results, this study employs a winsorizing method at the 0.5th and 99.5th percentiles to handle extreme values. Newey-West robust t-statistics are reported for different regression coefficients.

Tables 7, 8, and 9 present the Fama-Macbeth regression results when using $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$,

Table 7: Fama–MacBeth Cross-Sectional Regressions-$\widehat{DS}_{t,i}^{|\beta|}$

	$\bar{\beta}_{t,i}^{abs}$	$\widehat{DS}_{t,i}^{\|\beta\|}$	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
	-0.130***	-0.239***	-0.103***	-0.056***	-0.203***	-0.146***	-0.254***	0.041	0.022	-0.044*	0.171***	-0.263***	-0.198***	-0.074***	-0.080***	0.019
	-9.75	-10.6	-4.73	-2.74	-12	-6.86	-10.69	1.13	0.5	-1.94	7.49	-14.02	-10.79	-2.9	-4.15	1.21
	$\bar{\beta}_{t,i}^{abs}$	$\widehat{DS}_{t,i}^{\|\beta\|}$	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
M1	-0.074***	-0.201***	-0.079*	0.031												
	-4.21	-8.14	-1.9	0.79												
M2	-0.013				-0.051***	-0.071***	-0.332***	-0.014	0.057*	-0.111***	0.127***	-0.251***	0.064***	0.057**	0.068**	-0.006
	-1.56				-5.54	-4.33	-8.43	-0.52	1.72	-6.06	6.84	-16.64	3.18	2.03	2.19	-0.22
M3		-0.102***			-0.048***	-0.060***	-0.334***	-0.008	0.058*	-0.109***	0.125***	-0.233***	0.087***	0.043	0.073**	-0.004
		-6.53			-5.26	-3.69	-8.53	-0.31	1.76	-5.96	6.74	-16.13	4.58	1.57	2.4	-0.14
M4			-0.033**		-0.053***	-0.060***	-0.333***	-0.005	0.054	-0.108***	0.118***	-0.248***	0.066***	0.049*	0.070**	-0.006
			-2.01		-5.78	-3.84	-8.63	-0.2	1.63	-6	6.69	-16.89	3.5	1.76	2.34	-0.23
M5				-0.068***	-0.065***	-0.051***	-0.332***	-0.004	0.054	-0.106***	0.111***	-0.246***	0.066***	0.04	0.071**	-0.005
				-4.36	-7	-3.24	-8.87	-0.15	1.61	-5.89	6.26	-16.84	3.51	1.45	2.41	-0.19
M6	-0.076***	-0.187***	0.218***	-0.287***	-0.220***											
	-4.51	-7.79	5.51	-7.97	-13.72											
M7	-0.080***	-0.169***	-0.062	0.037		-0.093***										
	-4.74	-7.49	-1.53	0.97		-5.01										
M8	-0.054***	-0.183***	0.153***	-0.233***			-0.255***									
	-3.46	-7.48	4.35	-7.27			-10.55									
M9	-0.075***	-0.199***	-0.093**	0.039				0.04								
	-4.44	-8.27	-2.3	1.02				1.24								
M10	-0.073***	-0.197***	-0.087**	0.031					0.031							
	-4.49	-8.03	-2.23	0.87					0.75							
M11	-0.072***	-0.201***	-0.097**	0.041						-0.056***						
	-4.25	-8.4	-2.39	1.1						-2.66						
M12	-0.073***	-0.212***	-0.036	0.029							0.139***					
	-4.15	-8.76	-0.96	0.78							6.39					
M13	-0.095***	-0.098***	-0.065	0.04								-0.223***				
	-5.75	-4.67	-1.58	1.06								-13.98				
M14	-0.071***	-0.156***	0	-0.046									-0.123***			
	-4.28	-6.64	-0.01	-1.28									-7.79			
M15	-0.064***	-0.218***	-0.027	-0.048										-0.122***		
	-3.98	-9.91	-0.7	-1.34										-5.33		
M16	-0.080***	-0.193***	-0.079*	0.026											-0.047***	
	-4.72	-8.14	-1.94	0.67											-2.59	
M17	-0.078***	-0.197***	-0.073*	0.024												0.009
	-4.48	-8.12	-1.8	0.63												0.62
M18	-0.072***	-0.092***	0.259***	-0.308***	-0.097***	-0.052***	-0.336***	0.001	0.047	-0.104***	0.116***	-0.229***	0.083***	0.033	0.070**	-0.005
	-5.86	-5.35	8.67	-10.43	-9.82	-3.43	-8.86	0.03	1.43	-5.9	6.63	-16.6	4.53	1.21	2.41	-0.22

and $\widehat{AutoCorr}_{t,i}^{|\beta|}$ as measures of dispersion. In Panel A, we focus on simple univariate regressions, where each regression includes stock returns and a single explanatory variable. Panel B shows the results of simultaneous regressions controlling for multiple variables. In the regression results of Panel A, univariate sorting portfolio results are slightly different. For $\bar{\beta}_{t,i}^{abs}$, $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$, these factors still exhibit highly significant risk premiums, although the estimated risk premiums are relatively small. $\bar{\beta}_{t,i}^{abs}$ is about 13 basis points per week with a robust t-statistic absolute value of 9.75. $\widehat{DS}_{t,i}^{|\beta|}$ and $\widehat{Range}_{t,i}^{|\beta|}$ show a highly similar trend, with risk premiums and robust t-statistic absolute values around 24 basis points and 11 per week, respectively. In comparison, $\widehat{AutoCorr}_{t,i}^{|\beta|}$ has smaller risk premiums and t-statistic absolute values, approximately 4 basis points and 5 per week, respectively.

Now, turning to Panel B, for $\bar{\beta}_{t,i}^{abs}$, regardless of the accompanying measure of dispersion, in the M1 model, i.e., without adding any other beta-type factors, its risk premium drops to an insignificant level. However, in other models, its risk premium remains at the 1% significance level, with robust t-statistic absolute values exceeding 6, and risk premiums absolute values exceeding 7. This indicates that the pricing ability of $\bar{\beta}_{t,i}^{abs}$ can be jointly explained by multiple factors, and its pricing ability is restored when other beta-type factors are simultaneously added. Correspondingly,

Table 8: Fama–MacBeth Cross-Sectional Regressions-$\widehat{Range}_{t,i}^{|\beta|}$

	$\bar{\beta}_{t,i}^{abs}$	$\widehat{Range}_{t,i}^{|\beta|}$	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
	-0.130***	-0.240***	-0.103***	-0.056***	-0.203***	-0.146***	-0.254***	0.041	0.022	-0.044*	0.171***	-0.263***	-0.198***	-0.074***	-0.080***	0.019
	-9.75	-11.07	-4.73	-2.74	-12	-6.86	-10.69	1.13	0.5	-1.94	7.49	-14.02	-10.79	-2.9	-4.15	1.21
	$\bar{\beta}_{t,i}^{abs}$	$\widehat{Range}_{t,i}^{|\beta|}$	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
M1	-0.109***	-0.234***	0.023	-0.018												
	-7.45	-9.72	0.53	-0.47												
M2	-0.013				-0.051***	-0.071***	-0.332***	-0.014	0.057*	-0.111***	0.127***	-0.251***	0.064***	0.057**	0.068**	-0.006
	-1.56				-5.54	-4.33	-8.43	-0.52	1.72	-6.06	6.84	-16.64	3.18	2.03	2.19	-0.22
M3		-0.111***			-0.044***	-0.046***	-0.337***	-0.012	0.053	-0.109***	0.121***	-0.221***	0.090***	0.042	0.079***	-0.006
		-7.29			-4.89	-2.84	-8.51	-0.48	1.6	-6.02	6.52	-15.86	4.79	1.55	2.64	-0.25
M4			-0.033**		-0.053***	-0.060***	-0.333***	-0.005	0.054	-0.108***	0.118***	-0.248***	0.066***	0.049*	0.070**	-0.006
			-2.01		-5.78	-3.84	-8.63	-0.2	1.63	-6	6.69	-16.89	3.5	1.76	2.34	-0.23
M5				-0.068***	-0.065***	-0.051***	-0.332***	-0.004	0.054	-0.106***	0.111***	-0.246***	0.066***	0.04	0.071**	-0.005
				-4.36	-7	-3.24	-8.87	-0.15	1.61	-5.89	6.26	-16.84	3.51	1.45	2.41	-0.19
M6	-0.111***	-0.206***	0.286***	-0.313***	-0.206***											
	-7.89	-8.79	7.06	-9.12	-13.18											
M7	-0.108***	-0.208***	0.023	-0.006		-0.067***										
	-7.5	-9.06	0.54	-0.16		-3.65										
M8	-0.088***	-0.207***	0.230***	-0.267***			-0.245***									
	-6.77	-8.62	6.27	-8.71			-10.21									
M9	-0.108***	-0.235***	0.01	-0.009				0.02								
	-7.72	-10.1	0.24	-0.24				0.63								
M10	-0.107***	-0.233***	0.017	-0.018					0.01							
	-7.97	-9.65	0.43	-0.5					0.24							
M11	-0.106***	-0.239***	0.006	-0.007						-0.067***						
	-7.43	-10.23	0.15	-0.2						-3.19						
M12	-0.108***	-0.247***	0.068*	-0.02							0.136***					
	-7.48	-10.26	1.75	-0.55							6.1					
M13	-0.110***	-0.127***	-0.013	0.015								-0.194***				
	-7.69	-5.98	-0.3	0.4								-13.13				
M14	-0.100***	-0.201***	0.075*	-0.074**									-0.099***			
	-7.16	-8.7	1.85	-2.07									-6.55			
M15	-0.102***	-0.241***	0.072*	-0.100***										-0.129***		
	-7.46	-10.63	1.83	-2.95										-5.91		
M16	-0.109***	-0.231***	0.017	-0.019											-0.025	
	-7.69	-9.82	0.41	-0.5											-1.38	
M17	-0.109***	-0.233***	0.025	-0.022												-0.003
	-7.58	-9.79	0.6	-0.58												-0.21
M18	-0.086***	-0.106***	0.285***	-0.317***	-0.093***	-0.044***	-0.339***	-0.004	0.042	-0.105***	0.116***	-0.216***	0.088***	0.035	0.078***	-0.005
	-7.72	-6.13	9.17	-11.06	-9.36	-2.87	-8.71	-0.14	1.27	-5.95	6.61	-16.22	4.62	1.31	2.76	-0.22

Table 9: Fama–MacBeth Cross-Sectional Regressions-$\widehat{AutoCorr}_{t,i}^{|\beta|}$

	$\bar{\beta}_{t,i}^{abs}$	$\widehat{AutoCorr}_{t,i}^{|\beta|}$	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
	-0.130***	-0.037***	-0.103***	-0.056***	-0.203***	-0.146***	-0.254***	0.041	0.022	-0.044*	0.171***	-0.263***	-0.198***	-0.074***	-0.080***	0.019
	-9.75	-4.89	-4.73	-2.74	-12	-6.86	-10.69	1.13	0.5	-1.94	7.49	-14.02	-10.79	-2.9	-4.15	1.21
	$\bar{\beta}_{t,i}^{abs}$	$\widehat{AutoCorr}_{t,i}^{|\beta|}$	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
M1	-0.129***	-0.042***	-0.133***	0.033												
	-8.39	-6.08	-3.19	0.85												
M2	-0.013				-0.051***	-0.071***	-0.332***	-0.014	0.057*	-0.111***	0.127***	-0.251***	0.064***	0.057**	0.068**	-0.006
	-1.56				-5.54	-4.33	-8.43	-0.52	1.72	-6.06	6.84	-16.64	3.18	2.03	2.19	-0.22
M3		-0.027***			-0.053***	-0.071***	-0.337***	-0.015	0.058*	-0.112***	0.129***	-0.251***	0.062***	0.057**	0.069**	-0.007
		-4.72			-5.8	-4.32	-8.57	-0.57	1.75	-6.1	6.98	-16.66	3.19	2.02	2.22	-0.26
M4			-0.033**		-0.053***	-0.060***	-0.333***	-0.005	0.054	-0.108***	0.118***	-0.248***	0.066***	0.049*	0.070**	-0.006
			-2.01		-5.78	-3.84	-8.63	-0.2	1.63	-6	6.69	-16.89	3.5	1.76	2.34	-0.23
M5				-0.068***	-0.065***	-0.051***	-0.332***	-0.004	0.054	-0.106***	0.111***	-0.246***	0.066***	0.04	0.071**	-0.005
				-4.36	-7	-3.24	-8.87	-0.15	1.61	-5.89	6.26	-16.84	3.51	1.45	2.41	-0.19
M6	-0.128***	-0.038***	0.178***	-0.295***	-0.230***											
	-8.74	-5.51	4.44	-8.07	-14.4											
M7	-0.125***	-0.039***	-0.100**	0.04		-0.120***										
	-8.37	-5.78	-2.47	1.04		-5.91										
M8	-0.102***	-0.038***	0.115***	-0.242***			-0.269***									
	-7.55	-5.55	3.22	-7.5			-11.07									
M9	-0.129***	-0.041***	-0.147***	0.042				0.049								
	-8.75	-6.09	-3.64	1.1				1.49								
M10	-0.129***	-0.042***	-0.141***	0.033					0.044							
	-8.96	-5.98	-3.55	0.91					1.08							
M11	-0.126***	-0.039***	-0.150***	0.044						-0.050**						
	-8.45	-5.69	-3.73	1.17						-2.33						
M12	-0.129***	-0.048***	-0.096**	0.032							0.143***					
	-8.45	-6.96	-2.49	0.86							6.65					
M13	-0.123***	-0.034***	-0.080**	0.042								-0.250***				
	-8.31	-5.36	-2	1.11								-13.91				
M14	-0.107***	-0.040***	-0.013	-0.066*									-0.166***			
	-7.41	-6.03	-0.33	-1.86									-9.97			
M15	-0.124***	-0.042***	-0.102***	-0.024										-0.080***		
	-8.55	-6.14	-2.58	-0.67										-3.12		
M16	-0.132***	-0.039***	-0.130***	0.028											-0.067***	
	-8.83	-6.06	-3.23	0.74											-3.64	
M17	-0.130***	-0.041***	-0.128***	0.028												0.016
	-8.62	-6.16	-3.15	0.75												1.06
M18	-0.092***	-0.027***	0.247***	-0.311***	-0.099***	-0.057***	-0.338***	-0.004	0.049	-0.106***	0.116***	-0.243***	0.066***	0.045	0.066**	-0.007
	-8.34	-4.95	8.39	-10.8	-9.89	-3.67	-8.72	-0.17	1.49	-5.99	6.62	-16.91	3.41	1.62	2.25	-0.29

all three measures of dispersion maintain significant excess returns at the 1% significance level in which model, consistent with the results of the previous double sorting. $\widehat{DS}_{t,i}^{|\beta|}$ and $\widehat{Range}_{t,i}^{|\beta|}$ exhibit larger risk premiums and t-statistic values, while $\widehat{AutoCorr}_{t,i}^{|\beta|}$ has smaller values. These results suggest that the degree of dispersion of the differences in market risk borne by investors in different market conditions has a more pronounced impact on pricing compared to the dispersion of these differences themselves.

6 Betting against Diverse beta Factors: Performance analysis of strategies

To better assess the economic significance of the factors, this section presents the performance of trading strategies constructed using six beta-type factors. These six factors include realized beta, down-side semi-beta, $\bar{\beta}_{t,i}^{abs}$, $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$. As shown in the results of the single-variable grouping in Section 4.1, all six beta factors exhibit negative pricing abilities. Therefore, in constructing the investment strategy, we extract the first group from the single-variable grouping in an equally weighted manner to build the long position. Similarly, we use the same method to construct the short position of the last group to obtain a zero-cost investment portfolio. The portfolio is rebalanced weekly, and to ensure the authenticity of the strategy returns, we choose to use simple interest rather than compound interest when calculating the net asset value of the portfolio.

To make our portfolio more realistic, we consider the losses brought about by transaction costs when evaluating the performance of the strategy. According to the method proposed by Bandi et al. (2008), the calculation of the portfolio return adjusted for transaction costs is as follows:

$$netR_{t+1}^{p} = R_{t+1}^{p} - \rho \sum_{\{i=1\}}^{n} \left(1 + R_{t+1}^{i}\right) \left|\Delta\omega_{t+1}^{i}\right|$$

where ρ is the proportion of transaction costs to turnover, R_{t+1}^{p} is the unadjusted portfolio return for week $t+1$, $netR_{t+1}^{p}$ is the portfolio return for week $t+1$ adjusted for transaction costs, R_{t+1}^{j} is the unadjusted return for asset j, $\Delta\omega_{t+1}^{i} = \omega_{t+1}^{i} - \omega_{t}^{i}$, and ω_{t}^{i} is defined as the investment weight of asset i in week t. After considering the tax situation in the A-share market, we decided to set ρ to 0.002, i.e., two basis points, and consider charging fees on both sides.

Table 10 presents the average returns and corresponding performance indicators such as robust t-statistics, standard deviation, Sharpe ratio, etc., for various strategies. The average weekly returns

Table 10: Performance analysis of diverse beta strategies

	beta	Down-side beta	$\bar{\beta}^{abs}_{t,i}$	$\widehat{DS}^{\lvert\beta\rvert}_{t,i}$	$\widehat{Range}^{\lvert\beta\rvert}_{t,i}$	$\widehat{AutoCorr}^{\lvert\beta\rvert}_{t,i}$
Avg ret	0.0025	0.0013	0.003	0.0039	0.005	0.0007
	4.3368	2.3205	8.0045	7.2574	8.8771	3.1268
SR	0.1391	0.0719	0.2805	0.2389	0.2969	0.1046
beta_mkt	-1.1864	-1.1571	0.0456	-0.7953	-0.7246	0.1089
	-12.3242	-12.8051	0.7708	-8.934	-7.8573	2.7007
beta_vmg	0.9707	0.8343	0.0929	0.9399	1.0144	0.0086
	4.1278	3.9624	0.5986	4.5275	4.4312	0.1206
beta_smb	0.2983	0.0201	0.1952	0.2036	0.1739	0.009
	1.3075	0.0918	1.5002	1.1019	0.7952	0.1611
Alpha	0.0037	0.0023	0.0029	0.0045	0.0056	0.0006
	6.5421	4.3911	7.916	8.4038	9.5289	2.4574
Adj R2	0.3429	0.3529	0.0042	0.2409	0.2053	0.014

for realized beta, down-side beta, $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, and $\widehat{AutoCorr}^{|\beta|}_{t,i}$ strategies are 25, 13, 30, 39, 50, and 7 basis points, respectively, all significantly at the 1% level. The Sharpe ratios are 0.14, 0.07, 0.28, 0.24, 0.30, and 0.1, respectively. It is worth noting that, except for $\widehat{AutoCorr}^{|\beta|}_{t,i}$, the performance of the strategies for the other three factors is superior to realized beta and down-side semi-beta when considering both average returns and Sharpe ratios.

Additionally, we also conduct contemporaneous explanatory regressions of strategy returns on the CH3 multifactor model to analyze the style exposure of strategy returns and whether they can achieve alpha excess returns that the multifactor model cannot explain. The results of this analysis are also shown in Table 10. All six beta-type factors can obtain significant alpha returns, with $\widehat{Range}^{|\beta|}_{t,i}$ having the highest excess return of 56 basis points per week. The investment strategy constructed using $\bar{\beta}^{abs}_{t,i}$ has no significant risk exposure on the MKT, VMG, and SMB factors, resulting in a low R^2, indicating that its returns are highly independent of the CH3 factor model. For the other beta-type factors, their portfolio returns have a highly significant negative exposure to the market factor (MKT), except for $\widehat{AutoCorr}^{|\beta|}_{t,i}$. Surprisingly, except for $\bar{\beta}^{abs}_{t,i}$ and $\widehat{AutoCorr}^{|\beta|}_{t,i}$, the other factor measures also have very significant positive exposure to VMG, i.e., the value factor, indicating that these beta-type factors seem to prefer a value style.

To visually demonstrate the performance of the strategies over the entire sample period, Figure 2 shows the net value curves for each strategy. The x-axis represents the trading dates, ranging from mid-2005 to the end of 2022, while the y-axis represents the strategy net value, ranging from

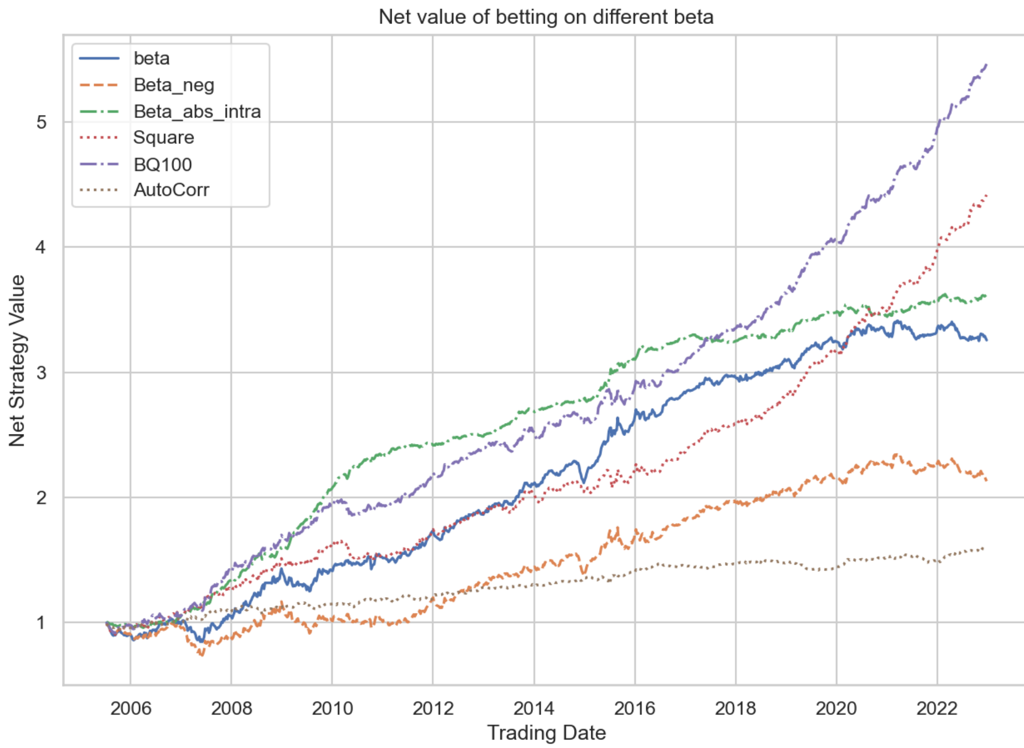

Figure 2: Cumulative returns for long-short portfolio strategies

0 to 6. These curves clearly illustrate the changes in net value for each strategy over time. It is evident that in the initial years, the strategy based on $\bar{\beta}_{t,i}^{abs}$ led the pack but was subsequently overtaken by $\widehat{Range}_{t,i}^{|\beta|}$ and $\widehat{DS}_{t,i}^{|\beta|}$. Both $\bar{\beta}_{t,i}^{abs}$ and $\widehat{Range}_{t,i}^{|\beta|}$ consistently outperformed realized beta and down-side semi-beta. Overall, this figure demonstrates that the new indicators proposed in this study, which measure the systematic risk differences and their degree of dispersion in different market conditions, outperform traditional realized beta and down-side semi-beta in generating superior long-short strategy returns, adding practical and economic significance.

7 Robust test

To further validate the robustness of our conclusions, we conducted a series of additional empirical studies. In our previous analyses, we chose the CSI 300 as a proxy for the market index, as it is the most liquid and widely followed broad-based index in the current market. However, since the constituents of the CSI 300 are mainly large-cap blue-chip stocks, estimating intraday market beta for small-cap stocks might introduce bias. To ensure that this potential bias does not affect our empirical results, in this section, we used high-frequency intraday trading data for the Shanghai Composite Index (SHCI) and the Shenzhen Component Index (SZCI). We constructed a comprehensive A-share index, referred to as the All-A Share Composite Index, using a market-cap-weighted approach. We recalibrated the estimation of intraday market beta for individual stocks using this All-A Share Composite Index as the market proxy and examined the effectiveness of the factors.

Additionally, considering the construction error in variable construction in cross-sectional pricing regressions due to beta estimation errors, we analyzed the sensitivity of our main empirical results to the intraday sampling frequency. We extended the rolling estimation of intraday beta from 25 data points to 15, 20, 25, and 30 data points, covering four different rolling intervals, to estimate intraday beta. This was done to ensure that our empirical results are not influenced by the size of the rolling estimation window. Figure 3 and Table 11 present the time series plots of 5-minute closing prices for the CSI 300, SHCI, SZCI, and the All-A Share Composite Index, as well as the correlation matrix of index returns. It can be observed that there are some differences in the closing price trends between the All-A Share Composite Index and the CSI 300, and the correlation coefficient between their returns is 0.88, indicating the presence of distinct information between them. By estimating intraday market beta using the All-A Share Composite Index and validating the effectiveness of the factors, we effectively enhance the robustness of our empirical results.

Table 11: 5-minute return correlation of different market indices

	close_300	close_szzz	close_szcz	close_A
close_300	1	0.9709	0.943	0.8881
close_szzz	0.9709	1	0.9096	0.8941
close_szcz	0.943	0.9096	1	0.8791
close_A	0.8881	0.8941	0.8791	1

Tables 12 and 13 respectively present the single-variable sorting results for $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, and $\widehat{AutoCorr}^{|\beta|}_{t,i}$ under different rolling estimation intervals for the CSI 300 and the All-A Share Composite Index. Different panels represent different choices of rolling estimation intervals. For the same index and different rolling estimation intervals, we observe that as the rolling estimation interval gradually increases, although there is a small decrease in the magnitude of HML excess returns and their significance, all four factors maintain highly significant negative pricing power across all four rolling intervals, whether for the CSI 300 or the All-A Share Composite Index.

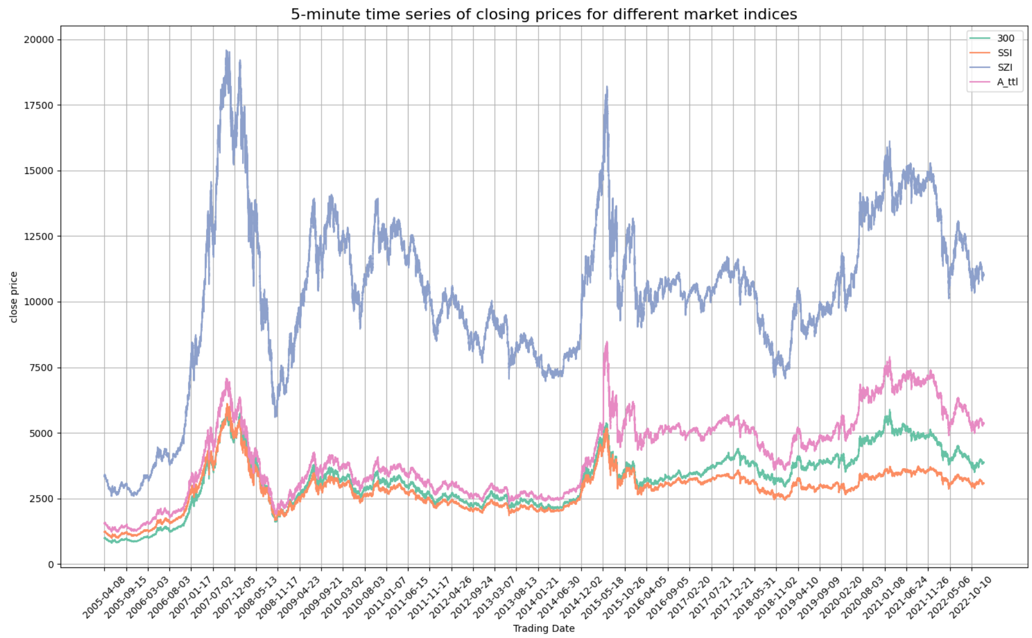

Figure 3: 5-minute time series of closing prices for different market indices

We further observe that $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, and $\widehat{Range}^{|\beta|}_{t,i}$ consistently exhibit higher excess returns and significance levels compared to $\widehat{AutoCorr}^{|\beta|}_{t,i}$. Additionally, with the increase in the rolling estimation interval, there is a noticeable decline in $\widehat{AutoCorr}^{|\beta|}_{t,i}$. This phenomenon is normal since $\widehat{AutoCorr}^{|\beta|}_{t,i}$ relies on intraday available data for autocorrelation calculations. As the rolling estimation window becomes larger, the amount of data available for autocorrelation calculations decreases, leading to greater bias in the calculated autocorrelation. Nevertheless, even with this effect, $\widehat{AutoCorr}^{|\beta|}_{t,i}$ remains significantly robust, especially when the rolling estimation interval is 30. Moreover, there is no significant difference in the single-variable sorting results between different benchmark indices, indicating strong robustness in our results for single-variable sorting.

Tables 12 and 13 respectively present the single-variable sorting results for $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, $\widehat{Range}^{|\beta|}_{t,i}$, and $\widehat{AutoCorr}^{|\beta|}_{t,i}$ under different rolling estimation intervals for the CSI 300 and the All-A Share Composite Index. Different panels represent different choices of rolling estimation intervals. For the same index, different rolling estimation intervals show some variations. Although there is a slight decrease in the magnitude of HML excess returns and their significance, as the rolling estimation interval gradually increases, all four factors maintain highly significant negative pricing power across all four rolling intervals, whether for the CSI 300 or the All-A Share Composite Index. Furthermore, we notice that $\bar{\beta}^{abs}_{t,i}$, $\widehat{DS}^{|\beta|}_{t,i}$, and $\widehat{Range}^{|\beta|}_{t,i}$ consistently exhibit higher excess returns and significance levels compared to $\widehat{AutoCorr}^{|\beta|}_{t,i}$. Additionally, with the increase in

Table 12: Robust Predictive Single-Sorted Portfolios for CSI300

	$\bar{\beta}^{abs}_{t,i}$		$\widehat{DS}^{\lvert\beta\rvert}_{t,i}$		$\widehat{Range}^{\lvert\beta\rvert}_{t,i}$		$\widehat{AutoCorr}^{\lvert\beta\rvert}_{t,i}$	
	AvgRet	Alpha	AvgRet	Alpha	AvgRet	Alpha	AvgRet	Alpha
Panel A: Rolling window 15								
G01	0.2217	-0.1476	0.2946	-0.042	0.3058	-0.0357	0.1955	-0.1731
G02	0.2712	-0.1021	0.2902	-0.0726	0.3173	-0.05	0.1874	-0.1976
G03	0.2402	-0.1373	0.2437	-0.1306	0.2589	-0.1138	0.1737	-0.2077
G04	0.1752	-0.1989	0.1619	-0.2239	0.1598	-0.2231	0.1484	-0.2236
G05	-0.1133	-0.4748	-0.1954	-0.5919	-0.2467	-0.6383	0.0899	-0.259
HML	-0.3349	-0.3272	-0.4899	-0.5499	-0.5525	-0.6026	-0.1056	-0.0859
t	-8.6054	-8.6412	-8.74	-9.6924	-9.6185	-10.1821	-5.1129	-3.9718
Panel B: Rolling window 20								
G01	0.2197	-0.1467	0.2821	-0.0523	0.3158	-0.023	0.1776	-0.1914
G02	0.2679	-0.1086	0.2668	-0.0937	0.2991	-0.0665	0.2054	-0.1754
G03	0.2397	-0.1366	0.2446	-0.1287	0.2521	-0.1222	0.1719	-0.2079
G04	0.1774	-0.1964	0.1658	-0.2225	0.165	-0.2183	0.1478	-0.2287
G05	-0.1099	-0.4725	-0.1644	-0.5637	-0.2371	-0.631	0.092	-0.2577
HML	-0.3296	-0.3258	-0.4465	-0.5114	-0.5529	-0.6079	-0.0856	-0.0664
t	-8.7	-8.7728	-8.2463	-9.2674	-9.6745	-10.3388	-4.0023	-3.052
Panel C: Rolling window 25								
G01	0.2162	-0.1507	0.2719	-0.0588	0.3179	-0.0201	0.1899	-0.1798
G02	0.2712	-0.1054	0.2563	-0.1068	0.3008	-0.0623	0.1759	-0.2041
G03	0.2358	-0.1391	0.2405	-0.1323	0.2498	-0.1274	0.169	-0.2087
G04	0.1757	-0.197	0.163	-0.2279	0.1347	-0.2492	0.1626	-0.2105
G05	-0.1039	-0.4687	-0.1366	-0.5349	-0.2081	-0.6018	0.0976	-0.2579
HML	-0.3201	-0.318	-0.4084	-0.4762	-0.526	-0.5816	-0.0922	-0.0781
t	-8.7767	-8.7442	-7.7539	-8.8424	-9.3549	-9.9708	-4.3299	-3.4475
Panel D: Rolling window 30								
G01	0.2131	-0.1552	0.2639	-0.0658	0.3247	-0.0168	0.1788	-0.1929
G02	0.2723	-0.1004	0.255	-0.1085	0.29	-0.0732	0.1764	-0.2025
G03	0.2351	-0.1401	0.2267	-0.1487	0.2452	-0.13	0.1861	-0.194
G04	0.1754	-0.1992	0.1667	-0.2233	0.1412	-0.2412	0.1553	-0.2156
G05	-0.1007	-0.4658	-0.1173	-0.5146	-0.2061	-0.5996	0.0984	-0.2559
HML	-0.3138	-0.3106	-0.3812	-0.4488	-0.5307	-0.5828	-0.0804	-0.0629
t	-8.5972	-8.4944	-7.1931	-8.3186	-9.6945	-10.3703	-3.1116	-2.4055

Table 13: Robust Predictive Single-Sorted Portfolios for CSI All-A

	$\bar{\beta}^{abs}_{t,i}$		$\widehat{DS}^{\lvert\beta\rvert}_{t,i}$		$\widehat{Range}^{\lvert\beta\rvert}_{t,i}$		$\widehat{AutoCorr}^{\lvert\beta\rvert}_{t,i}$	
	AvgRet	Alpha	AvgRet	Alpha	AvgRet	Alpha	AvgRet	Alpha
Panel A: Rolling window 15								
G01	0.2252	-0.1457	0.2955	-0.0428	0.3194	-0.0228	0.1965	-0.1735
G02	0.2783	-0.0979	0.2853	-0.0824	0.3124	-0.0575	0.1846	-0.2034
G03	0.2375	-0.1424	0.2578	-0.1191	0.2683	-0.1121	0.1788	-0.2067
G04	0.1784	-0.1997	0.1631	-0.2262	0.1594	-0.2275	0.1539	-0.2225
G05	-0.1029	-0.4699	-0.1853	-0.585	-0.2431	-0.6357	0.1026	-0.2494
HML	-0.3281	-0.3242	-0.4808	-0.5423	-0.5624	-0.6129	-0.0939	-0.0759
t	-8.8727	-9.0385	-8.5673	-9.4456	-9.7499	-10.1822	-4.0852	-3.2925
Panel B: Rolling window 20								
G01	0.2261	-0.1434	0.2852	-0.0519	0.3203	-0.0233	0.1798	-0.1891
G02	0.2783	-0.1001	0.268	-0.0939	0.2995	-0.0682	0.2033	-0.1829
G03	0.2355	-0.1444	0.2535	-0.1276	0.266	-0.1121	0.1755	-0.2076
G04	0.1808	-0.1958	0.1684	-0.2216	0.1604	-0.2283	0.1592	-0.2188
G05	-0.104	-0.4717	-0.1584	-0.5604	-0.2296	-0.6235	0.0988	-0.2572
HML	-0.3301	-0.3284	-0.4436	-0.5086	-0.5499	-0.6003	-0.081	-0.0682
t	-9.0632	-9.3601	-8.1056	-9.0406	-9.7605	-10.2378	-3.5267	-2.9536
Panel C: Rolling window 25								
G01	0.2216	-0.1474	0.2753	-0.06	0.3215	-0.0219	0.1865	-0.1846
G02	0.2767	-0.1023	0.263	-0.1008	0.2991	-0.0679	0.1839	-0.2022
G03	0.241	-0.1375	0.2454	-0.1317	0.2538	-0.124	0.1807	-0.1997
G04	0.1774	-0.1986	0.1696	-0.2254	0.1488	-0.2401	0.1681	-0.2082
G05	-0.1002	-0.4698	-0.1369	-0.5377	-0.2068	-0.6018	0.0972	-0.2608
HML	-0.3218	-0.3224	-0.4122	-0.4777	-0.5283	-0.5799	-0.0892	-0.0762
t	-8.8713	-9.041	-7.7715	-8.7482	-9.4044	-9.8602	-4.2614	-3.5252
Panel D: Rolling window 30								
G01	0.2182	-0.1518	0.2613	-0.0747	0.3289	-0.0149	0.1808	-0.1918
G02	0.276	-0.1004	0.263	-0.1001	0.2988	-0.0687	0.1878	-0.1952
G03	0.2425	-0.1371	0.2374	-0.1423	0.2379	-0.1397	0.1901	-0.1925
G04	0.1703	-0.204	0.1713	-0.2224	0.1568	-0.2314	0.1565	-0.2185
G05	-0.0905	-0.4623	-0.1164	-0.516	-0.2059	-0.6009	0.1012	-0.2575
HML	-0.3087	-0.3105	-0.3777	-0.4413	-0.5348	-0.586	-0.0796	-0.0657
t	-8.515	-8.6523	-7.0569	-8.2029	-9.7649	-10.2943	-3.3345	-2.7686

the rolling estimation interval, there is a noticeable decline in $\widehat{AutoCorr}_{t,i}^{|\beta|}$. This phenomenon is normal since $\widehat{AutoCorr}_{t,i}^{|\beta|}$ relies on intraday available data for autocorrelation calculations. As the rolling estimation window becomes larger, the amount of data available for autocorrelation calculations decreases, leading to greater bias in the calculated autocorrelation. Nevertheless, even with this effect, $\widehat{AutoCorr}_{t,i}^{|\beta|}$ remains significantly robust, especially when the rolling estimation interval is 30. Moreover, there is no significant difference in the single-variable sorting results between different benchmark indices, indicating strong robustness in our results for single-variable sorting.

Table 14: Robust Predictive Double-Sorted Portfolios for CSI300

		BM	ME	MOM	REV	IVOL	ILLIQ	MAX	MIN	CSK	CKT	RSJ	beta	Down-side beta	Discon beta
Panel A: $\bar{\beta}_{t,i}^{abs}$															
RW:15	HML	-0.3431***	-0.3452***	-0.3474***	-0.0674***	-0.3195***	-0.3269***	-0.1921***	-0.2681***	-0.3391***	-0.3216***	-0.1135***	-0.3218***	-0.379***	-0.3317***
	Alpha	-0.3378***	-0.3333***	-0.3416***	-0.0662**	-0.3149***	-0.3161***	-0.18***	-0.2739***	-0.3304***	-0.3145***	-0.1117***	-0.3104***	-0.3984***	-0.3235***
RW:20	HML	-0.3399***	-0.332***	-0.3335***	-0.0789***	-0.315***	-0.3151***	-0.1911***	-0.2604***	-0.327***	-0.317***	-0.1075***	-0.3123***	-0.361***	-0.3268***
	Alpha	-0.3388***	-0.3254***	-0.3304***	-0.0794***	-0.312***	-0.3055***	-0.1812***	-0.2686***	-0.3207***	-0.315***	-0.1081***	-0.3052***	-0.3818***	-0.3219***
RW:25	HML	-0.3381***	-0.3232***	-0.3262***	-0.0774***	-0.2967***	-0.3079***	-0.1881***	-0.2592***	-0.3212***	-0.3094***	-0.1091***	-0.3022***	-0.3638***	-0.3104***
	Alpha	-0.3373***	-0.316***	-0.3238***	-0.0815***	-0.2956***	-0.2992***	-0.178***	-0.2698***	-0.3163***	-0.308***	-0.1125***	-0.2955***	-0.3856***	-0.3078***
RW:30	HML	-0.3246***	-0.3168***	-0.3223***	-0.0673***	-0.2917***	-0.3002***	-0.1813***	-0.2526***	-0.3079***	-0.3009***	-0.0983***	-0.2963***	-0.3587***	-0.3038***
	Alpha	-0.3241***	-0.3087***	-0.3211***	-0.0729***	-0.2913***	-0.2917***	-0.1743***	-0.2641***	-0.3037***	-0.2996***	-0.1044***	-0.2889***	-0.3812***	-0.3004***
Panel B: $\widehat{DS}_{t,i}^{|\beta|}$															
RW:15	HML	-0.4935***	-0.5082***	-0.5024***	-0.363***	-0.2501***	-0.4396***	-0.3018***	-0.4994***	-0.4804***	-0.4806***	-0.3734***	-0.3525***	-0.4186***	-0.3656***
	Alpha	-0.5519***	-0.5617***	-0.5496***	-0.4169***	-0.2999***	-0.4799***	-0.3547***	-0.5461***	-0.5358***	-0.5412***	-0.4347***	-0.3506***	-0.4368***	-0.3949***
RW:20	HML	-0.4555***	-0.4541***	-0.462***	-0.3358***	-0.2064***	-0.3908***	-0.2558***	-0.4561***	-0.4279***	-0.4346***	-0.3433***	-0.2947***	-0.3721***	-0.3254***
	Alpha	-0.5212***	-0.5125***	-0.5138***	-0.3932***	-0.2629***	-0.4389***	-0.3135***	-0.508***	-0.4876***	-0.502***	-0.4088***	-0.2988***	-0.3964***	-0.3619***
RW:25	HML	-0.4201***	-0.4192***	-0.4257***	-0.3002***	-0.1846***	-0.3661***	-0.2186***	-0.4312***	-0.3947***	-0.4005***	-0.3186***	-0.2667***	-0.3384***	-0.2924***
	Alpha	-0.4881***	-0.4802***	-0.4803***	-0.3587***	-0.2434***	-0.419***	-0.2795***	-0.484***	-0.4571***	-0.4692***	-0.3871***	-0.2741***	-0.364***	-0.3298***
RW:30	HML	-0.3881***	-0.3896***	-0.3939***	-0.2742***	-0.1576***	-0.3445***	-0.1856***	-0.4072***	-0.3753***	-0.3702***	-0.2999***	-0.2343***	-0.3005***	-0.2698***
	Alpha	-0.4547***	-0.4507***	-0.4475***	-0.3302***	-0.2159***	-0.3972***	-0.2459***	-0.4615***	-0.4369***	-0.4379***	-0.367***	-0.2456***	-0.3255***	-0.3072***
Panel C: $\widehat{Range}_{t,i}^{|\beta|}$															
RW:15	HML	-0.5733***	-0.5759***	-0.5797***	-0.4238***	-0.3046***	-0.4974***	-0.3832***	-0.5668***	-0.5464***	-0.542***	-0.4296***	-0.4352***	-0.5092***	-0.4386***
	Alpha	-0.623***	-0.6215***	-0.6145***	-0.4694***	-0.3405***	-0.5265***	-0.4218***	-0.6091***	-0.5929***	-0.5895***	-0.4823***	-0.4171***	-0.5107***	-0.458***
RW:20	HML	-0.565***	-0.5675***	-0.5568***	-0.4099***	-0.2868***	-0.4921***	-0.361***	-0.5518***	-0.5314***	-0.5349***	-0.4329***	-0.4028***	-0.4946***	-0.4386***
	Alpha	-0.6181***	-0.6171***	-0.5953***	-0.4589***	-0.3273***	-0.5243***	-0.4039***	-0.5958***	-0.5815***	-0.585***	-0.4903***	-0.3917***	-0.5005***	-0.4584***
RW:25	HML	-0.5284***	-0.5437***	-0.5389***	-0.395***	-0.2857***	-0.4656***	-0.3464***	-0.5379***	-0.5063***	-0.5091***	-0.4069***	-0.4021***	-0.4725***	-0.4177***
	Alpha	-0.5832***	-0.5941***	-0.579***	-0.4489***	-0.3286***	-0.4988***	-0.3909***	-0.5847***	-0.5582***	-0.5621***	-0.4662***	-0.3873***	-0.4799***	-0.4431***
RW:30	HML	-0.5428***	-0.5357***	-0.54***	-0.4057***	-0.2781***	-0.4672***	-0.359***	-0.5363***	-0.5106***	-0.5209***	-0.4096***	-0.421***	-0.4779***	-0.4124***
	Alpha	-0.594***	-0.5836***	-0.5769***	-0.4524***	-0.3185***	-0.4961***	-0.3986***	-0.5778***	-0.558***	-0.5736***	-0.4642***	-0.4052***	-0.4823***	-0.4299***
Panel D: $\widehat{AutoCorr}_{t,i}^{|\beta|}$															
RW:15	HML	-0.0976***	-0.1028***	-0.0898***	-0.094***	-0.0802***	-0.1281***	-0.0958***	-0.0925***	-0.0892***	-0.0992***	-0.0982***	-0.1131***	-0.1111***	-0.1035***
	Alpha	-0.0795***	-0.0924***	-0.0693***	-0.0734***	-0.0611***	-0.1175***	-0.0757***	-0.0731***	-0.071***	-0.0803***	-0.0772***	-0.1014***	-0.097***	-0.0852***
RW:20	HML	-0.0832***	-0.0807***	-0.0675***	-0.0717***	-0.07***	-0.1069***	-0.0772***	-0.0823***	-0.0763***	-0.0891***	-0.0796***	-0.0938***	-0.0893***	-0.081***
	Alpha	-0.0655***	-0.0688***	-0.0493**	-0.0531***	-0.0529***	-0.0954***	-0.0615***	-0.0626***	-0.0612***	-0.0731***	-0.0595***	-0.0836***	-0.0741***	-0.0634***
RW:25	HML	-0.0838***	-0.0896***	-0.08***	-0.0891***	-0.0818***	-0.1083***	-0.0914***	-0.0893***	-0.0836***	-0.0859***	-0.0855***	-0.0923***	-0.0913***	-0.0862***
	Alpha	-0.0692***	-0.0823***	-0.0672***	-0.0775***	-0.0676***	-0.1013***	-0.0778***	-0.0746***	-0.0718***	-0.0732***	-0.0707***	-0.0844***	-0.0831***	-0.0716***
RW:30	HML	-0.0811***	-0.0841***	-0.0794***	-0.0781***	-0.0657***	-0.1005***	-0.08***	-0.0741***	-0.0771***	-0.0744***	-0.0702***	-0.0775***	-0.0775***	-0.067***
	Alpha	-0.0631**	-0.0742***	-0.0615**	-0.0668***	-0.0491*	-0.0899***	-0.0625***	-0.0576**	-0.0609**	-0.0583**	-0.0555**	-0.0657***	-0.0688***	-0.0507**

Tables 16 and 17 present the Fama-Macbeth regression results under different rolling estimation intervals, with $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$ as measures of dispersion, while controlling for all control variables. Different panels represent different measures of dispersion indicators. Similar to the results of the sorting approach, as the rolling estimation interval increases, there is a slight decline in the risk premium and significance of the core factors. However, for both the CSI 300 and the All-A Share Composite Index, these factors still exhibit significantly negative risk

Table 15: Robust Predictive Double-Sorted Portfolios for CSI All-A

		BM	ME	MOM	REV	IVOL	ILLIQ	MAX	MIN	CSK	CKT	RSJ	beta	Down-side beta	Discon beta
Panel A: $\bar{\beta}^{abs}_{t,i}$															
RW:15	HML	-0.3375***	-0.3354***	-0.3345***	-0.0667***	-0.3123***	-0.3161***	-0.1852***	-0.2689***	-0.3241***	-0.322***	-0.1145***	-0.3054***	-0.3762***	-0.3241***
	Alpha	-0.3369***	-0.3275***	-0.3309***	-0.0679***	-0.3092***	-0.3084***	-0.1736***	-0.2786***	-0.3195***	-0.3187***	-0.1164***	-0.2984***	-0.3955***	-0.3194***
RW:20	HML	-0.34***	-0.3297***	-0.3322***	-0.0773***	-0.3062***	-0.3084***	-0.192***	-0.2683***	-0.3247***	-0.3187***	-0.1164***	-0.3055***	-0.3658***	-0.3187***
	Alpha	-0.3403***	-0.3244***	-0.3303***	-0.0807***	-0.306***	-0.302***	-0.1813***	-0.278***	-0.3223***	-0.3181***	-0.1192***	-0.299***	-0.3872***	-0.3181***
RW:25	HML	-0.3281***	-0.3216***	-0.3282***	-0.0741***	-0.3019***	-0.3026***	-0.1871***	-0.2579***	-0.3226***	-0.3084***	-0.1119***	-0.3064***	-0.36***	-0.3086***
	Alpha	-0.3299***	-0.3183***	-0.3294***	-0.0784***	-0.3038***	-0.2988***	-0.1788***	-0.2705***	-0.3218***	-0.3113***	-0.1166***	-0.3017***	-0.3848***	-0.3101***
RW:30	HML	-0.3187***	-0.3104***	-0.316***	-0.0557**	-0.2912***	-0.288***	-0.182***	-0.2465***	-0.3092***	-0.2955***	-0.0977***	-0.2963***	-0.3527***	-0.292***
	Alpha	-0.3218***	-0.3068***	-0.3173***	-0.061**	-0.2932***	-0.2837***	-0.1765***	-0.2605***	-0.308***	-0.2962***	-0.1053***	-0.2924***	-0.3785***	-0.2927***
Panel B: $\widehat{DS}^{\lvert\beta\rvert}_{t,i}$															
RW:15	HML	-0.4881***	-0.4943***	-0.4914***	-0.3617***	-0.245***	-0.4307***	-0.2883***	-0.4998***	-0.4688***	-0.4723***	-0.3802***	-0.3405***	-0.4124***	-0.3599***
	Alpha	-0.5501***	-0.5518***	-0.5377***	-0.4179***	-0.2935***	-0.4757***	-0.3398***	-0.5488***	-0.5251***	-0.5325***	-0.4425***	-0.3412***	-0.4315***	-0.3895***
RW:20	HML	-0.448***	-0.4576***	-0.4624***	-0.3314***	-0.2013***	-0.395***	-0.2522***	-0.4572***	-0.4263***	-0.432***	-0.3361***	-0.2849***	-0.358***	-0.3164***
	Alpha	-0.511***	-0.5167***	-0.512***	-0.3922***	-0.2568***	-0.4447***	-0.3114***	-0.5095***	-0.4861***	-0.4983***	-0.4038***	-0.2932***	-0.381***	-0.3512***
RW:25	HML	-0.4131***	-0.4179***	-0.4283***	-0.2965***	-0.1812***	-0.3654***	-0.2237***	-0.4243***	-0.3995***	-0.3937***	-0.3164***	-0.2522***	-0.3277***	-0.2817***
	Alpha	-0.4766***	-0.4779***	-0.4818***	-0.3582***	-0.2397***	-0.4172***	-0.283***	-0.4777***	-0.4599***	-0.4608***	-0.3828***	-0.2629***	-0.3521***	-0.3201***
RW:30	HML	-0.3821***	-0.3806***	-0.389***	-0.2663***	-0.1567***	-0.3351***	-0.191***	-0.4032***	-0.3708***	-0.3667***	-0.2932***	-0.2313***	-0.2917***	-0.2664***
	Alpha	-0.4449***	-0.4404***	-0.4391***	-0.3243***	-0.2117***	-0.3865***	-0.2461***	-0.4561***	-0.4318***	-0.4335***	-0.3587***	-0.2439***	-0.3166***	-0.3027***
Panel C: $\widehat{Range}^{\lvert\beta\rvert}_{t,i}$															
RW:15	HML	-0.5675***	-0.5751***	-0.5815***	-0.4247***	-0.3094***	-0.4974***	-0.3898***	-0.5738***	-0.5365***	-0.5508***	-0.4434***	-0.4247***	-0.4986***	-0.4483***
	Alpha	-0.617***	-0.6212***	-0.616***	-0.4693***	-0.3446***	-0.5275***	-0.4278***	-0.615***	-0.5835***	-0.6012***	-0.4967***	-0.4131***	-0.5035***	-0.4651***
RW:20	HML	-0.5564***	-0.5703***	-0.5556***	-0.4218***	-0.2944***	-0.4936***	-0.3682***	-0.554***	-0.5271***	-0.5287***	-0.4381***	-0.4103***	-0.4824***	-0.4312***
	Alpha	-0.6065***	-0.6174***	-0.5906***	-0.4689***	-0.3316***	-0.5242***	-0.4105***	-0.5953***	-0.5756***	-0.5803***	-0.4914***	-0.3998***	-0.4875***	-0.4498***
RW:25	HML	-0.5357***	-0.5495***	-0.5382***	-0.3936***	-0.2879***	-0.4709***	-0.3538***	-0.5322***	-0.5096***	-0.5208***	-0.418***	-0.3975***	-0.4713***	-0.4188***
	Alpha	-0.5874***	-0.5958***	-0.5754***	-0.4449***	-0.3286***	-0.5019***	-0.392***	-0.5752***	-0.5573***	-0.573***	-0.4727***	-0.3832***	-0.4764***	-0.4392***
RW:30	HML	-0.5399***	-0.5426***	-0.5476***	-0.4114***	-0.2804***	-0.4726***	-0.3535***	-0.5306***	-0.5096***	-0.5132***	-0.4204***	-0.4107***	-0.465***	-0.4122***
	Alpha	-0.5911***	-0.5892***	-0.584***	-0.4568***	-0.3195***	-0.5034***	-0.3903***	-0.5712***	-0.5552***	-0.5659***	-0.4734***	-0.3968***	-0.4694***	-0.4295***
Panel D: $\widehat{AutoCorr}^{\lvert\beta\rvert}_{t,i}$															
RW:15	HML	-0.0908***	-0.0971***	-0.0837***	-0.0867***	-0.0763***	-0.1199***	-0.0877***	-0.0903***	-0.0822***	-0.0942***	-0.0877***	-0.1103***	-0.0981***	-0.0978***
	Alpha	-0.0761***	-0.0889***	-0.0661***	-0.0687***	-0.06***	-0.1117***	-0.0687***	-0.0752***	-0.0663***	-0.0768***	-0.0687***	-0.102***	-0.0853***	-0.0815***
RW:20	HML	-0.0718***	-0.0764***	-0.0647***	-0.0604***	-0.0617***	-0.096***	-0.0618***	-0.0706***	-0.0647***	-0.0649***	-0.0684***	-0.0871***	-0.08***	-0.075***
	Alpha	-0.0592***	-0.0706***	-0.0534**	-0.045**	-0.0506**	-0.0892***	-0.0465**	-0.0562***	-0.0534***	-0.0529**	-0.0535**	-0.0846***	-0.0722***	-0.0611***
RW:25	HML	-0.08***	-0.0909***	-0.0749***	-0.0714***	-0.0697***	-0.1006***	-0.0752***	-0.0799***	-0.0772***	-0.0791***	-0.083***	-0.0903***	-0.0859***	-0.0823***
	Alpha	-0.0684***	-0.0861***	-0.0621***	-0.0605***	-0.059***	-0.0928***	-0.0616***	-0.0656***	-0.0677***	-0.0682***	-0.0691***	-0.0821***	-0.0782***	-0.0698***
RW:30	HML	-0.0718***	-0.0772***	-0.0622***	-0.0709***	-0.0685***	-0.0944***	-0.0753***	-0.0723***	-0.0735***	-0.0795***	-0.0633***	-0.0743***	-0.0715***	-0.0709***
	Alpha	-0.0592***	-0.0699***	-0.0494**	-0.0614***	-0.0554**	-0.0852***	-0.0631***	-0.0569***	-0.0626***	-0.0667***	-0.0495**	-0.0649***	-0.0635***	-0.0565***

premiums at the 1% significance level across all rolling intervals. This consistency between the Fama-Macbeth regression results and the portfolio sorting results indicates a high level of robustness in our findings.

8 Conclusions

This paper, by relaxing the assumption of constant intraday beta in traditional asset pricing literature, delves into the differences in investors' systematic risk exposure and its dispersion under different market conditions, as well as the explanatory power of these differences for cross-sectional stock returns and their impact on risk premiums. Building on Bollerslev et al. (2022), we construct $\bar{\beta}_{t,i}^{abs}$ as a measure of semi-beta differences under different market conditions and simultaneously create three different intraday dispersion measures: $\widehat{DS}_{t,i}^{|\beta|}$, $\widehat{Range}_{t,i}^{|\beta|}$, and $\widehat{AutoCorr}_{t,i}^{|\beta|}$. Through various empirical methods, we demonstrate their significant pricing ability for stocks and their ability to generate substantial risk premiums, offering practical economic value.

This observation is particularly significant for measuring semi-beta differences under different market conditions, especially for $\widehat{DS}_{t,i}^{|\beta|}$ and $\widehat{Range}_{t,i}^{|\beta|}$. It further confirms the sensitivity of these two indicators in revealing systematic risk differences, indicating that they provide powerful measures of semi-beta differences under different market conditions. These metrics demonstrate strong capabilities in capturing the heterogeneity of systematic risk in market fluctuations, emphasizing the importance of considering the influence of market states in explaining dynamic changes in investors' risk exposure. This underscores the critical role of incorporating market conditions when interpreting investment strategies and the volatility of cross-sectional stock returns.

In summary, the main contributions of this paper are: firstly, providing a more comprehensive understanding of the dynamic changes in intraday systematic risk by relaxing the assumptions in traditional beta pricing literature; secondly, expanding the application of high-frequency beta in asset pricing research from the perspective of investors' systematic risk exposure under different market conditions; and finally, offering a new entry point for high-frequency factor pricing research in the A-share market, providing additional perspectives and theoretical support for explaining differences in cross-sectional stock returns.

A Appendix: Control Variables

Our empirical study employs the following control variables and firm characteristics. All variables are computed by taking weekly averages after obtaining daily observations:

Table 16: Robust Fama–MacBeth Cross-Sectional Regressions for CSI300

	$\bar{\beta}^{abs}_{t,i}$	Dispersion	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
Panel A: Dispersion measure in terms of $\widehat{DS}^{\lvert\beta\rvert}_{t,i}$																
RW:15	-0.059***	-0.130***	0.249***	-0.286***	-0.092***	-0.050***	-0.328***	0.002	0.044	-0.103***	0.117***	-0.218***	0.085***	0.026	0.073**	-0.006
	-4.98	-6.84	8.26	-9.88	-9.27	-3.31	-8.99	0.08	1.33	-5.86	6.67	-16.01	4.6	1.02	2.52	-0.23
RW:20	-0.066***	-0.107***	0.253***	-0.298***	-0.095***	-0.051***	-0.333***	0.001	0.046	-0.104***	0.117***	-0.225***	0.084***	0.03	0.072**	-0.005
	-5.54	-5.94	8.46	-10.19	-9.61	-3.38	-8.86	0.06	1.39	-5.89	6.65	-16.41	4.51	1.12	2.47	-0.21
RW:25	-0.072***	-0.092***	0.259***	-0.308***	-0.097***	-0.052***	-0.336***	0.001	0.047	-0.104***	0.116***	-0.229***	0.083***	0.033	0.070**	-0.005
	-5.86	-5.35	8.67	-10.43	-9.82	-3.43	-8.86	0.03	1.43	-5.9	6.63	-16.6	4.53	1.21	2.41	-0.22
RW:30	-0.078***	-0.086***	0.269***	-0.320***	-0.099***	-0.053***	-0.337***	0	0.047	-0.105***	0.116***	-0.230***	0.083***	0.033	0.070**	-0.005
	-6.31	-5.24	8.99	-10.73	-9.93	-3.46	-8.82	0.02	1.45	-5.91	6.63	-16.6	4.5	1.22	2.4	-0.22
Panel B: Dispersion measure in terms of $\widehat{Range}^{\lvert\beta\rvert}_{t,i}$																
RW:15	-0.072***	-0.120***	0.268***	-0.293***	-0.088***	-0.044***	-0.335***	-0.002	0.039	-0.105***	0.116***	-0.212***	0.087***	0.032	0.080***	-0.004
	-6.57	-6.53	8.84	-10.39	-8.85	-2.89	-8.98	-0.09	1.19	-5.93	6.64	-15.95	4.76	1.23	2.84	-0.19
RW:20	-0.078***	-0.109***	0.274***	-0.304***	-0.091***	-0.044***	-0.338***	-0.003	0.04	-0.105***	0.117***	-0.215***	0.087***	0.034	0.081***	-0.003
	-7.15	-6.1	8.81	-10.76	-9.18	-2.92	-8.74	-0.12	1.23	-5.94	6.63	-16.21	4.6	1.27	2.84	-0.13
RW:25	-0.086***	-0.106***	0.285***	-0.317***	-0.093***	-0.044***	-0.339***	-0.004	0.042	-0.105***	0.116***	-0.216***	0.088***	0.035	0.078***	-0.005
	-7.72	-6.13	9.17	-11.06	-9.36	-2.87	-8.71	-0.14	1.27	-5.95	6.61	-16.22	4.62	1.31	2.76	-0.22
RW:30	-0.097***	-0.101***	0.303***	-0.338***	-0.095***	-0.044***	-0.337***	-0.004	0.043	-0.104***	0.116***	-0.217***	0.085***	0.035	0.077***	-0.005
	-8.7	-6.07	9.84	-11.66	-9.58	-2.91	-8.84	-0.17	1.33	-5.92	6.59	-16.36	4.63	1.31	2.7	-0.22
Panel C: Dispersion measure in terms of $\widehat{AutoCorr}^{\lvert\beta\rvert}_{t,i}$																
RW:15	-0.090***	-0.035***	0.234***	-0.297***	-0.096***	-0.057***	-0.336***	-0.003	0.047	-0.107***	0.117***	-0.243***	0.066***	0.045*	0.066**	-0.008
	-8.18	-6.55	8	-10.58	-9.57	-3.72	-8.8	-0.14	1.43	-5.99	6.69	-16.8	3.43	1.65	2.25	-0.31
RW:20	-0.091***	-0.030***	0.241***	-0.305***	-0.098***	-0.057***	-0.336***	-0.004	0.048	-0.107***	0.117***	-0.243***	0.065***	0.045	0.067**	-0.007
	-8.28	-5.66	8.19	-10.72	-9.76	-3.71	-8.7	-0.16	1.47	-6	6.66	-16.86	3.37	1.62	2.29	-0.28
RW:25	-0.092***	-0.027***	0.247***	-0.311***	-0.099***	-0.057***	-0.338***	-0.004	0.049	-0.106***	0.116***	-0.243***	0.066***	0.045	0.066**	-0.007
	-8.34	-4.95	8.39	-10.8	-9.89	-3.67	-8.72	-0.17	1.49	-5.99	6.62	-16.91	3.41	1.62	2.25	-0.29
RW:30	-0.095***	-0.026***	0.257***	-0.321***	-0.099***	-0.056***	-0.337***	-0.004	0.05	-0.106***	0.117***	-0.244***	0.065***	0.045	0.065**	-0.007
	-8.49	-4.63	8.67	-10.97	-9.97	-3.65	-8.76	-0.17	1.51	-5.99	6.63	-16.9	3.41	1.62	2.22	-0.28

Table 17: fRobust Fama–MacBeth Cross-Sectional Regressions for CSI All-A

	$\bar{\beta}^{abs}_{t,i}$	Dispersion	beta	Down-side beta	RSJ	Discon beta	REV	BM	ME	MOM	ILLIQ	IVOL	MAX	MIN	CSK	CKT
Panel A: Dispersion measure in terms of $\widehat{DS}^{\|\beta\|}_{t,i}$																
RW:15	-0.057***	-0.128***	0.264***	-0.303***	-0.094***	-0.050***	-0.298***	0.002	0.04	-0.103***	0.114***	-0.219***	0.063**	0.019	0.073**	-0.007
	-5.07	-6.72	9.15	-10.78	-9.67	-3.27	-6.51	0.1	1.23	-5.86	6.55	-16.04	2.47	0.7	2.56	-0.31
RW:20	-0.063***	-0.105***	0.267***	-0.313***	-0.097***	-0.051***	-0.301***	0.002	0.041	-0.104***	0.114***	-0.225***	0.062**	0.022	0.072**	-0.007
	-5.62	-5.87	9.36	-11.09	-10	-3.33	-6.49	0.08	1.27	-5.89	6.55	-16.37	2.43	0.78	2.52	-0.28
RW:25	-0.070***	-0.089***	0.273***	-0.323***	-0.099***	-0.052***	-0.303***	0.002	0.043	-0.104***	0.114***	-0.229***	0.061**	0.025	0.070**	-0.007
	-6.07	-5.23	9.53	-11.3	-10.21	-3.39	-6.55	0.06	1.31	-5.89	6.53	-16.55	2.46	0.84	2.45	-0.29
RW:30	-0.075***	-0.083***	0.282***	-0.334***	-0.100***	-0.053***	-0.305***	0.001	0.044	-0.104***	0.114***	-0.230***	0.061**	0.025	0.070**	-0.007
	-6.43	-5.09	9.71	-11.5	-10.32	-3.4	-6.59	0.03	1.34	-5.91	6.55	-16.59	2.48	0.86	2.44	-0.29
Panel B: Dispersion measure in terms of $\widehat{Range}^{\|\beta\|}_{t,i}$																
RW:15	-0.072***	-0.123***	0.286***	-0.311***	-0.089***	-0.044***	-0.306***	-0.002	0.036	-0.104***	0.114***	-0.212***	0.067**	0.026	0.081***	-0.006
	-6.88	-6.81	9.89	-11.35	-9.12	-2.85	-6.52	-0.07	1.11	-5.94	6.55	-15.91	2.56	0.92	2.89	-0.27
RW:20	-0.076***	-0.112***	0.290***	-0.319***	-0.092***	-0.044***	-0.310***	-0.002	0.037	-0.104***	0.115***	-0.215***	0.067**	0.028	0.080***	-0.005
	-7.35	-6.41	9.82	-11.67	-9.46	-2.88	-6.49	-0.1	1.13	-5.95	6.54	-16.16	2.54	0.97	2.87	-0.22
RW:25	-0.084***	-0.107***	0.302***	-0.333***	-0.095***	-0.044***	-0.311***	-0.003	0.039	-0.104***	0.114***	-0.216***	0.067**	0.029	0.078***	-0.007
	-7.95	-6.28	10.22	-12.03	-9.66	-2.88	-6.48	-0.12	1.19	-5.96	6.51	-16.18	2.57	1	2.77	-0.28
RW:30	-0.094***	-0.100***	0.320***	-0.355***	-0.097***	-0.045***	-0.310***	-0.004	0.041	-0.104***	0.114***	-0.218***	0.066**	0.029	0.076***	-0.007
	-8.79	-5.94	10.76	-12.54	-9.93	-2.91	-6.52	-0.15	1.24	-5.93	6.51	-16.38	2.52	1.02	2.72	-0.29
Panel C: Dispersion measure in terms of $\widehat{AutoCorr}^{\|\beta\|}_{t,i}$																
RW:15	-0.088***	-0.033***	0.248***	-0.314***	-0.098***	-0.057***	-0.303***	-0.003	0.044	-0.106***	0.116***	-0.243***	0.043	0.037	0.065**	-0.01
	-8.71	-6.09	8.87	-11.61	-9.96	-3.64	-6.29	-0.13	1.35	-5.98	6.6	-16.8	1.58	1.28	2.25	-0.4
RW:20	-0.089***	-0.028***	0.255***	-0.322***	-0.100***	-0.056***	-0.304***	-0.004	0.045	-0.106***	0.115***	-0.243***	0.043	0.037	0.067**	-0.009
	-8.74	-5.25	9.09	-11.78	-10.12	-3.63	-6.21	-0.15	1.38	-5.97	6.56	-16.84	1.53	1.25	2.3	-0.36
RW:25	-0.090***	-0.027***	0.260***	-0.327***	-0.100***	-0.056***	-0.305***	-0.004	0.046	-0.106***	0.114***	-0.244***	0.043	0.037	0.066**	-0.009
	-8.6	-4.97	9.23	-11.76	-10.24	-3.61	-6.31	-0.14	1.41	-5.97	6.53	-16.86	1.58	1.25	2.29	-0.36
RW:30	-0.094***	-0.028***	0.272***	-0.340***	-0.101***	-0.056***	-0.307***	-0.004	0.046	-0.106***	0.115***	-0.244***	0.044	0.037	0.065**	-0.009
	-8.74	-5.17	9.5	-11.95	-10.29	-3.58	-6.46	-0.16	1.42	-5.98	6.54	-16.86	1.63	1.26	2.26	-0.35

- Discontinuous Beta: $Discon\ beta = \widehat{\beta}_t^{(c,i)}$. Where $r_{s:\tau}^{(i)}$ and $r_{s:\tau}^{(0)}$ represent the returns of stock i and the market, respectively, at day s and intraday data point τ. Adapted from Bollerslev et al. (2016).

$$\widehat{\beta}_t^{(d,i)} = \sqrt{\frac{\sum_{s=t-l}^{t-1} \sum_{\tau=1}^{n} \left(r_{s:\tau}^{(i)} r_{s:\tau}^{(0)} \right)^2}{\sum_{s=t-l}^{t-1} \sum_{\tau=1}^{n} \left(r_{s:\tau}^{(0)} \right)^4}}$$

- Realized Semi-Jumps: RSJ_t. Relative sign jumps. Adapted from Bollerslev, Li, & Zhao (2020).

$$\mathrm{SJ}_t = \mathrm{RV}_t^+ - \mathrm{RV}_t^-, \quad \mathrm{RSJ}_t = \frac{\mathrm{SJ}_t}{\mathrm{RV}_t}$$

$$\mathrm{RV}_t^+ = \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbb{1}_{\{r,-1+i/n>0\}}, \quad \mathrm{RV}_t^- = \sum_{i=1}^{n} r_{t-1+i/n}^2 \mathbb{1}_{\{r,-1+i/n<0\}}$$

- Market Equity (ME): The average total market value of stocks over a week, $ME_t = \frac{1}{n} \sum_{i=t-n}^{t} Totle\_Marke$ Adapted from Fama & French (1993).

- Short-Term Reversal (REV): Measured using the total weekly returns of stocks. Adapted from Jegadeesh (1990).

- Momentum (MOM): The average returns of stocks from day $t-252$ to $t-22$. Adapted from Jegadeesh & Titman (1993).

- Maximum Daily Stock Returns (MAX): The maximum daily returns of stocks within a week. Adapted from Bali et al. (2011).

- Minimum Daily Stock Returns (MIN): The minimum daily returns of stocks within a week. Adapted from Bali et al. (2011).

- Idiosyncratic Volatility (IVOL): Standard deviation of residuals from the CH3 factor model by Liu et al. (2019) for excess stock returns from $t-20$ to t. Adapted from Ang, Hodrick, et al. (2006).

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \mathrm{MKT}_t + \gamma_i \mathrm{SMB}_t + \phi_i \mathrm{VMG}_t + \epsilon_{i,t} \tag{8}$$

- Stock Illiquidity (ILLIQ): Calculated as the absolute value of the stock's daily returns divided by its volume times the closing price. Adapted from Amihud (2002).

$$\mathrm{ILLIQ}_t = \frac{|r_{i,t}|}{\mathrm{volume}_{i,t} \times \mathrm{close}_{i,t}}$$

- Co-skewness (CSK): Where N is the number of trading days, $r_{i,d}$ and $r_{0,d}$ are the daily returns of stock i and the market portfolio on day d, and $\bar{r_{i,d}}$ and $\bar{r_{0,d}}$ are the corresponding means, estimated using a time window of $t-20$ to t. Adapted from Ang, Hodrick, et al. (2006).

$$\widehat{\mathrm{CSK}}_{i,t} = \frac{\frac{1}{N}\sum_d (r_{i,d}-\bar{r}_i)(r_{0,d}-\bar{r}_0)^2}{\sqrt{\frac{1}{N}\sum_d (r_{i,d}-\bar{r}_i)^2}\left(\frac{1}{N}\sum_d (r_{0,d}-\bar{r}_0)^2\right)}$$

- Co-kurtosis (CKT): Using variables consistent with CSK. Adapted from Ang, Hodrick, et al. (2006).

$$\widehat{\mathrm{CKT}}_{i,j} = \frac{\frac{1}{N}\sum_d (r_{i,d}-\bar{r}_i)(r_{0,d}-\bar{r}_0)^3}{\sqrt{\frac{1}{N}\sum_d (r_{i,d}-\bar{r}_i)^2}\left(\frac{1}{N}\sum_d (r_{0,d}-\bar{r}_0)^2\right)^{3/2}}$$

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