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Betting against beta with intraday and overnight signals

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ABSTRACT

The abnormal returns of the Betting Against Beta (BAB) strategy have attracted much interest among researchers and practitioners. Based on a market anomaly related to the Capital Asset Pricing Model, this strategy uses daily beta as a signal for portfolio construction. However, recent literature shows how some financial quantities, including beta, change between trading and non-trading periods. For this reason, we decided to compare the performance of the original BAB strategy with two BAB variants, where the signal for portfolio construction is given by intraday and overnight beta, respectively. Despite all strategies exhibiting positive cumulative returns, using the intraday beta signal leads to significantly higher performances. Further analyses show that the abnormal intraday BAB returns are mainly due to nano and micro-cap stocks which tend to outperform large-cap stocks, as well known from the literature.

1. Introduction

Rational agents select for their investments those portfolios with the highest expected excess return per unit of risk and therefore with a higher Sharpe ratio. The theory related to the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964) states that stocks with high beta values have higher market risk. For this reason, an investor should be compensated for risk through higher returns. Usually, the market overpays for high beta stocks and underpays for low beta stocks. Furthermore, investors overweight their portfolios towards higher beta assets and leverage their position to improve their returns. Nevertheless, as shown by many empirical tests (Black, 1972; Jensen, Black, & Scholes, 1972), high-risk stocks do not always give the extra returns that the theory predicts. The security market line, and thus the relationship between beta and returns, is sometimes flatter than suggested by the CAPM. During the last years, many authors tried to understand the causes of this anomaly, attributing it to inflation (Cohen, Polk, & Vuolteenaho, 2005), the influence of investors on funding restrictions (such as leverage constraints and margin requirements Frazzini & Pedersen, 2014), investor sentiment (i.e., disagreement Hong & Sraer, 2016, optimistic versus pessimistic periods Antoniou, Doukas, & Subrahmanyam, 2016, and regret aversion Qin, 2020). Considering these anomalies about investors and market behavior, starting from Black's work (Black, 1993), Frazzini and Pedersen (2014) developed a statistical arbitrage strategy known as Betting Against Beta (BAB). They constructed a factor that goes short on high beta stocks and, at the same time, allows to leverage the position by buying low beta stocks.

The high performance of this strategy gave the article enormous popularity among academics and practitioners. Starting from this result, several works developed new trading strategies and theories (Asness, Frazzini, Gormsen, & Pedersen, 2020; Bali, Brown, Murray, & Tang, 2017; Hendershott, Livdan, & Rösch, 2020; Liu, Stambaugh, & Yuan, 2018; Ma, Tee, & Li, 2022). In a recent article, Novy-Marx and Velikov (2022) confirm the abnormal returns attributed to the BAB strategy despite its high transaction costs, but criticized the non-standard procedures used in the factor construction (i.e., the rank-weighted portfolio construction, hedging by leveraging, beta evaluation technique).

Frazzini and Pedersen (2014) construct their BAB factor considering a rank weighting scheme, an alternative to the classical quantile organization. In this approach, they order all the stocks using the daily beta as a signal. As demonstrated by the recent literature, due to the announcement during the market closure and the different investor's behavior, returns, volatility, and beta show different values between trading and non-trading periods.[1] This paper aims to look at beta as a signal, exploiting the differences between its intraday and overnight behavior on the BAB strategy. Our work, in some ways, is similar to that of Hendershott et al. (2020), where they find that the CAPM holds overnight. Considering this result, they propose a trading strategy

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[1] News and events happening during market closure affect the next day open prices (Ahoniemi, Fuertes, & Olmo, 2015; Ham, Ryu, & Webb, 2022). Lou, Polk, and Skouras (2019) talk of a tug of war between intraday and overnight returns. Volatility seems to be higher during the intraday period (Linton & Wu, 2020). Insana (2022) find that daytime betas display higher values than overnight.

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consisting of betting on beta during the night while betting against beta during the trading period. Differently from them, we use the same strategy and methodology of Frazzini and Pedersen (2014) to understand if and how the use of the intraday and the overnight beta as signals have a different impact on the trading strategy. In particular, we compare the BAB returns obtained from three portfolios sorted and divided using the value of daily, intraday, and overnight pre-ranking betas as weights. In Section 2, we summarize the work of Frazzini and Pedersen (2014) and explain how we construct the weights for the intraday and overnight BAB factor evaluation. In Section 3, we present our results. Analyzing US stocks between 1997 to 2020, we find that the three BAB portfolios show different behaviors. Indeed, while they earn the same level of risk, the daily and intraday strategies provide higher returns and Sharpe ratio. In addition, at portfolio formation, the more profitable BAB strategies (i.e., daily and intraday) show a high (low) market capitalization on the long (short) position.

By implementing the CAPM (Lintner, 1965; Sharpe, 1964), the Fama and French (1992) three-factor model, and the Carhart (1997) four-factor model, we find that the alpha value, i.e., the portfolio performances, shows abnormal returns for all the BAB strategies, especially for the intraday one. Furthermore, we observe a negative relationship between the Market return (Mkt) and Small Minus Big (SMB) factors implying that the strategies move opposite to the market and favor large-cap stocks. We implement the same models also using ten portfolios organized considering the pre-ranking beta values on each trading period. We find that the alpha value decreases with beta in daily and intraday portfolios, i.e., portfolios with lower (higher) beta stocks have higher (lower) alpha.

2. Daily, intraday and overnight BAB factor

Considering the asset pricing effect of the funding friction, Frazzini and Pedersen (2014) evaluate the returns on a BAB factor providing an excess return on a self-financing portfolio, i.e., a portfolio that is long and short leveraged on low (L) and high (H) beta securities:

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}\left(r_{t+1}^L - r^f\right) - \frac{1}{\beta_t^H}\left(r_{t+1}^H - r^f\right) , \tag{1}$$

where r^f represents the risk-free rate, $r_{t+1}^L = r'_{t+1}w_L$, $r_{t+1}^H = r'_{t+1}w_H$ and $\beta_t^L = \beta'_{t+1}w_L$, $\beta_t^H = \beta'_{t+1}w_H$ ($\beta_t^L < \beta_t^H$) are the returns and betas associated with the portfolios constructed on low and high beta stocks. Their related weights w_L and w_H, are estimated considering the pre-ranking beta values. The resulting portfolio (1) is market neutral, i.e., has a beta equal to zero. Furthermore, the leveraging and deleveraging of the long and short portfolios, respectively, have been done considering a beta of one.

The crucial points of this strategy are the portfolio organization and the weights allocation based on daily pre-ranking beta values. Considering the different beta behavior between trading and non-trading periods, we decide to introduce two additional BAB portfolios. Taking inspiration from the original BAB procedure in (1), we create the two portfolios allocating the stocks according to the overnight and intraday pre-ranking beta values and compute the weights accordingly. We describe the various steps that lead to the construction of the trading strategies in what follows. For each trading period, at the end of each month, we rank all securities in ascending beta order and split them into two portfolios having low and high beta values. Following Frazzini and Pedersen (2014), we compute the pre-ranking beta using a standard rolling regression of the excess return on market return. We split beta computation into two parts: the correlation between stock and market returns and the ratio between returns and market standard deviations.

The daily, intraday, and overnight pre-ranking betas, of a generic security i, can be written as:

$$\hat{\beta}_i^d = \hat{\rho}^d \frac{\hat{\sigma}_i^d}{\hat{\sigma}_m^d}, \qquad \hat{\beta}_i^{id} = \hat{\rho}^{id} \frac{\hat{\sigma}_i^{id}}{\hat{\sigma}_m^{id}}, \qquad \hat{\beta}_i^{ov} = \hat{\rho}^{ov} \frac{\hat{\sigma}_i^{ov}}{\hat{\sigma}_m^{ov}} . \tag{2}$$

where $\hat{\sigma}_i^d$, $\hat{\sigma}_i^{id}$, $\hat{\sigma}_i^{ov}$ and $\hat{\sigma}_m^d$, $\hat{\sigma}_m^{id}$, $\hat{\sigma}_m^{ov}$ are the estimated daily, intraday, and overnight volatilities of the ith stock and the market, respectively, and $\hat{\rho}^d$, $\hat{\rho}^{id}$, $\hat{\rho}^{ov}$ are their correlation. While volatilities have fast windows (De Santis, Gerard, et al., 1997), correlations are slowly-moving, and thus we need more data to estimate them. In particular, we use a five years horizon to calculate correlations and a one-year rolling window standard deviation for volatilities. For this reason, we consider stocks with at least 120 trading days of non-missing data to compute volatilities and 750 observations for correlations.

Frazzini and Pedersen (2014), observed that in evaluating correlations, we also need to consider the financial market microstructure noise due to nonsynchronous trading. Indeed, in the presence of very liquid stocks and also considering that the market, by definition, is very liquid, the covariance between market and securities will tend to zero. To mitigate this problem, we evaluate correlations overlapping three daily log returns for the daily portfolio:

$$r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1 + r_{i,t+k}^d) , \tag{3}$$

while for the intraday and overnight we compute:

$$r_{i,t}^{3id} = \sum_{k=0}^{2} \ln(1 + r_{i,t+k}^{id}) , \quad r_{i,t}^{3ov} = \sum_{k=0}^{2} \ln(1 + r_{i,t+k}^{ov}) ,$$

where r^d, r^{id} and r^{ov} are the daily, intraday and overnight simple returns:

$$\begin{gathered} r_{i,t}^d = \frac{p_{i,t}^{close}}{p_{i,t-1}^{close}} - 1 , \\ r_{i,t}^{id} = \frac{p_{i,t}^{close}}{p_{i,t}^{open}} - 1 , \quad r_{i,t}^{ov} = \frac{p_{i,t}^{open}}{p_{i,t-1}^{close}} - 1 . \end{gathered} \tag{4}$$

We consider a beta-compression method to reduce the influence of the outliers and improve the accuracy of the evaluated betas. In particular, following Elton, Gruber, Brown, and Goetzmann (2009) and Vasicek (1973), we use a shrinkage beta estimator to combine market and stock betas. At each period, we adjust the beta of a generic stock i as:

$$\hat{\beta}_i = v_i \hat{\beta}_{i,TS} + (1 - v_i)\hat{\beta}_{XS} \tag{5}$$

where $\hat{\beta}_{i,TS}$ is the time series estimate of beta and $\hat{\beta}_{XS}$ represents the market beta that can be evaluated as the cross-sectional mean. v_i is a weight given by:

$$v_i = \frac{\sigma_{XS}^2}{\sigma_{i,TS}^2 + \sigma_{XS}^2} \tag{6}$$

where σ_{XS}^2 is beta cross-sectional variance at time t and $\sigma_{i,TS}^2$ is the variance of beta related to the stock i at time t. We compute three beta values regressing daily, intraday, and overnight returns on market return considering a five years rolling windows on returns. Despite the weight v_i is different for each stock, following the prescription usually adopted in the literature, we estimate a constant adjustment factor value to be attributed to all stocks. Considering the formulas (5) and (6) we use a different cross-sectional beta and weight for each trading period. In particular we adopt: $\hat{\beta}_{XS}^d = 0.96$, $\hat{\beta}_{XS}^{id} = 0.91$, $\hat{\beta}_{XS}^{ov} = 0.74$ and $v^d = 0.55$, $v^{id} = 0.58$, $v^{ov} = 0.50$.

After we obtain the daily, intraday, and overnight pre-ranking betas for each trading period, we evaluate the rank vectors as:

$$z_i^d = rank(\beta_{i,t}^d) , \qquad z_i^{id} = rank(\beta_{i,t}^{id}) , \qquad z_i^{ov} = rank(\beta_{i,t}^{ov}) ,$$

and compute the weights for short and long portfolio like

$$w_H = k(z - \bar{z})^+ , \quad w_L = k(z - \bar{z})^- \quad \text{with} \quad k = \frac{2}{1_n}|z - \bar{z}| \tag{7}$$

where $(\cdot)^+$ and $(\cdot)^-$ indicate the positive and negative part of the vectors $((\cdot)^+ = \max(0, \cdot)$, $(\cdot)^- = \max(0, -\cdot))$. k is a normalization factor ensuring

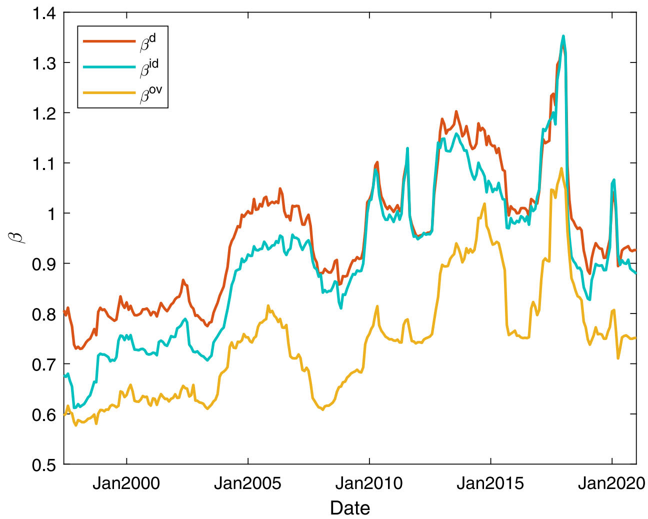

Fig. 1. Monthly average of the pre-ranking beta. For the BAB portfolio construction, at the end of each month, we evaluate daily, intraday, and overnight pre-ranking beta using a rolling regression of the excess return on market return.

that the weights sum to one. Afterward, we compute the daily, intraday, and overnight BAB factors using Eq. (1). To keep portfolio beta neutral, we need to use daily values of beta and returns in computing β_t^H, β_t^L and r_{t+1}^H, r_{t+1}^L. Therefore, the only difference among the portfolio strategies will be given by the values of the weights, that are computed according to the trading period.

3. Data and results

In our empirical analysis, we consider US stocks, from June 15, 1992, to December 31, 2020. Daily data come from the CRSP (Center of Research in Security Prices) database.[2] We examine the whole cross-section of stocks and discard those securities showing less than 120 observations for volatilities and 750 for correlations. This dataset pre-processing is needed due to the pre-ranking betas evaluation procedure, i.e., we compute correlations on a five-year and volatilities on a one-year rolling window (for this reason we show the results starting from 1997). For completeness, in Appendix A, we test the robustness of our results considering other time horizons. There, we show that changing the rolling window size does not affect the strategy and the results presented in the main body of this paper. Furthermore, in the pre-ranking evaluation, we keep only those stocks with open and closing prices to consider the same number of securities in the daily, intraday, and overnight portfolios and fairly compare the trading strategies. We adjust open and closing prices for dividends and splits by the cumulative adjustment factor (CFACPR) of the CRSP database. Furthermore, we exclude all days where the absolute value of returns is higher than 100%. For the evaluation of the excess return, we use the treasury bill rate provided by Kenneth French's library[3] as risk-free rate.

The computation of daily, intraday, and overnight pre-ranking betas requires to evaluate market returns on each trading period. To do so, we construct three specific market indexes tailored to the trading period and weighted by market capitalization.

The daily, intraday, and overnight pre-ranking beta are used as signals in portfolio formation and behave differently over the whole time series without highlighting any clear pattern (see Fig. 1). Despite

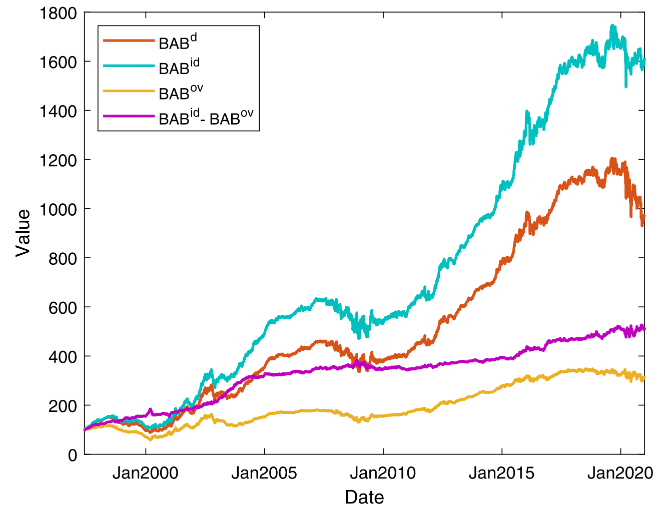

Fig. 2. Cumulative BAB portfolio returns. We evaluate the cumulative values of the daily, intraday, and overnight BAB factors and the difference between the intraday and overnight BAB returns.

Table 1
Main statistics on BAB returns. Values of annualized returns, annualized volatility, and Sharpe ratio of the BAB returns on three portfolios: daily, intraday, overnight, and the difference between the intraday and overnight BAB returns.

BAB Returns	BAB^d	BAB^{id}	BAB^{ov}	$BAB^{id} - BAB^{ov}$
Num. of stocks	3693	3693	3693	3693
Returns	0.0965	0.1180	0.0485	0.0695
Volatility	0.1254	0.1258	0.1051	0.0618
Sharpe	0.7698	0.9383	0.4613	1.1253

Table 2
Correlation between BAB returns. We evaluate the correlation between the returns of daily, intraday, and overnight BAB portfolios, and the difference between the intraday and overnight BAB returns.

Correlation BAB returns	BAB^d	BAB^{id}	BAB^{ov}	$BAB^{id} - BAB^{ov}$
BAB^d	1			
BAB^{id}	0.9669	1		
BAB^{ov}	0.9256	0.8718	1	
$BAB^{id} - BAB^{ov}$	0.3937	0.5526	0.0734	1

the different methods used in the beta evaluation, these results are similar to those from Insana (2022). There, estimating beta during the trading and non-trading period and considering a weighted ordinary least square with a kernel around time, they find lower overnight beta values between 2000 to 2020.

Following the approach of Section 2, we construct three BAB portfolios considering the values of daily, intraday, and overnight beta at the end of each month. We denote the portfolio returns with BAB^d, BAB^{id} and BAB^{ov}. The whole strategy considers 11 084 stocks between June 2, 1997, and December 31, 2020. Each portfolio contains, on average, 3693 stocks per month, 1846 on long and 1846 on short positions.

Comparing the performance of the three BAB portfolios (Table 1), we find that the intraday portfolio provides the highest returns, although its volatility is similar to the daily one. The overnight portfolio, instead, shows lower volatility but also lower returns. Therefore it seems that the most relevant contribution to the abnormal returns of the BAB strategy occurs during the trading period. These results are confirmed by looking at the cumulative returns in Fig. 2. Although the intraday and overnight BAB strategies have very different performances (i.e., the former has a much higher premium), they have a high correlation (Table 2). By evaluating the difference between the returns of

[2] http://www.crsp.com/.
[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

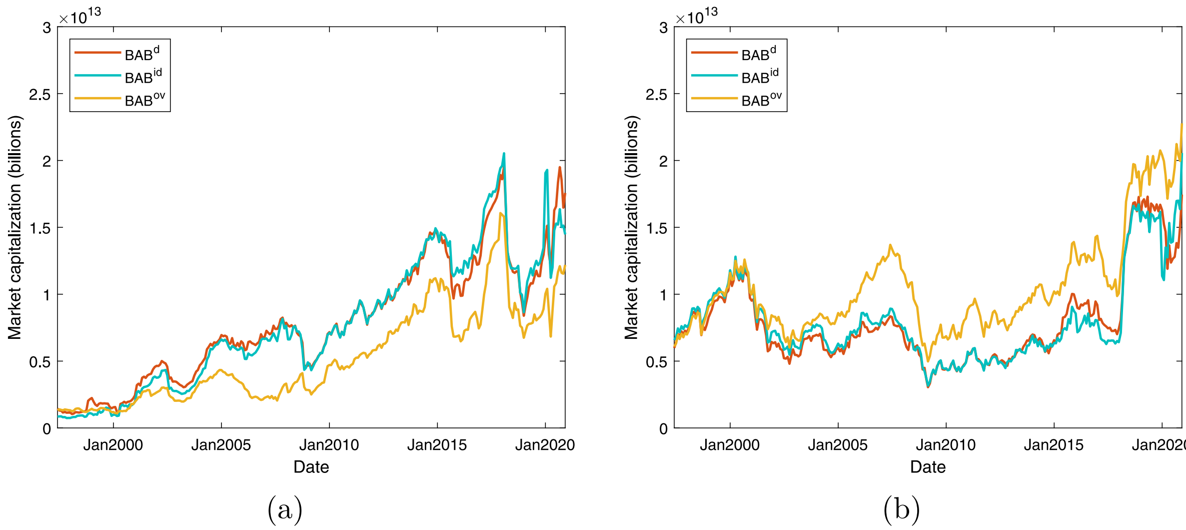

Fig. 3. Market capitalization at portfolio formation. At portfolio formation, we evaluate the market capitalization of long (low betas) (a) and short (high betas) (b) positions of the daily, intraday, and overnight BAB portfolios.

Table 3
Factor models on BAB portfolios. We evaluate alpha and beta by regressing daily BAB excess returns on different factors. First, we consider the excess market return as an explanatory variable, i.e., the classical CAPM. Then Fama and French's (1992) three-factor model, where the factors are excess market return (Mkt), value (SMB), and book to market (HML). And finally, we evaluate a four-factor model adding to the previous regressors the daily factor related to momentum (MOM). In parenthesis, below the coefficient estimates, we display t-statistics. We represent in bold the values with a 5% statistical significance.

BAB portfolios	CAPM		3-Factor Model				4-Factor model				
	α	Mkt	α	Mkt	SMB	HML	α	Mkt	SMB	HML	MOM
BAB^d	**4.28E−04**	**−3.48E−01**	**4.43E−04**	**−3.39E−01**	**−2.69E−01**	**−9.69E−02**	**3.51E−04**	**−2.77E−01**	**−2.75E−01**	**1.23E−01**	**3.50E−01**
	(5.01)	(−51.09)	(5.39)	(−51.49)	(−20.34)	(−8.48)	(4.89)	(−46.84)	(−23.84)	(11.03)	(43.31)
BAB^{id}	**5.26E−04**	**−3.85E−01**	**5.41E−04**	**−3.77E−01**	**−2.51E−01**	**−3.05E−02**	**4.58E−04**	**−3.22E−01**	**−2.57E−01**	**1.66E−01**	**3.13E−01**
	(6.45)	(−59.17)	(6.84)	(−59.77)	(−19.79)	(−2.78)	(6.51)	(−55.62)	(−22.70)	(15.17)	(39.49)
BAB^{ov}	**2.09E−04**	**−2.67E−01**	**2.18E−04**	**−2.61E−01**	**−1.48E−01**	**−9.83E−02**	**1.47E−04**	**−2.14E−01**	**−1.53E−01**	**7.04E−02**	**2.68E−01**
	(2.82)	(−45.21)	(2.99)	(−44.94)	(−12.68)	(−9.73)	(2.23)	(−39.43)	(−14.42)	(6.86)	(36.13)
$BAB^{id} - BAB^{ov}$	**2.41E−04**	**−1.17E−01**	**2.47E−04**	**−1.16E−01**	**−1.03E−01**	**6.75E−02**	**2.36E−04**	**−1.08E−01**	**−1.04E−01**	**9.54E−02**	**4.44E−02**
	(5.15)	(−31.50)	(5.44)	(−31.94)	(−14.09)	(10.69)	(5.21)	(−29.08)	(−14.28)	(13.55)	(8.72)

the two strategies (Table 1), $BAB^{id} - BAB^{ov}$, we still obtain a portfolio with a significant return, although lower than intraday and overnight. On the other hand, we see that volatility drops to almost half of its value, increasing the Sharpe ratio and thus providing a good leverage strategy.

The annualized Sharpe ratios of the various strategies are listed in Table 1. The intraday BAB strategy shows the highest value. We test the equality of the Sharpe ratios related to the BAB strategies considering the studentized circular block bootstrap approach of Ledoit and Wolf (2008), adopting 4999 bootstrap replications for computing the p-value and an optimal block-length. We find that the daily and intraday Sharpe ratios are statistically different (Appendix B Table B.1), i.e., we reject the null hypotheses of equality (p-value = 0.0048). Instead, the Sharpe ratio value of the strategy given by the difference between the intraday and overnight BAB returns is not statistically different from the daily and intraday ones.

Looking at the value of market capitalization of our long and short positions Fig. 3 at the end of the months, we notice that short stocks, i.e., high beta stocks, have a higher value at the beginning of the series. Instead, at the end of the series, all portfolios have a similar market capitalization, with an increasing trend for the long portfolio. If we look at the differences among the three portfolios, we notice how the more profitable strategies (i.e., the daily and the intraday one) form portfolios with a similar market capitalization. In particular, using daily and intraday signals creates portfolios with high market capitalization for the long position and low market capitalization for the short portfolio. This behavior does not appear in the overnight strategy. These results imply that stock size influences BAB strategies.

Considering the returns on the three BAB portfolios and the portfolio given by the difference between the BAB intraday and overnight returns, we want to study their relationship using some classical factors, like excess market return (Mkt), size (SMB), book to market (HML), and momentum (MOM). For this reason, we implement a classical Capital Asset Pricing Model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964), a Fama and French (1992) three-factor model, and a Carhart (1997) four-factor model. We use the daily factors provided by Kenneth French's library[4] in all these regressions.

Looking at Table 3, we observe a positive and statistically significant alpha for all the portfolio returns. Market returns and the Small Minus Big factors are negatively related to the four portfolios in all regressions. This finding means that the returns obtained applying the BAB strategy show an opposite relationship with the market, independently of the signal (i.e., when the market goes down, the BAB strategy is more profitable). Furthermore, in the three and four-factor models, the negative coefficient associated with the SMB factor implies that high market capitalization stocks influence portfolios more. The relationship between portfolio returns and stocks' value is not completely clear from our analysis. Indeed, evaluating the three-factor model, we find negative coefficients related to the HLM factor for all portfolios (i.e., low book-to-market stocks influence the BAB portfolio returns). At the same time, the four-factor model produces a positive

[4] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

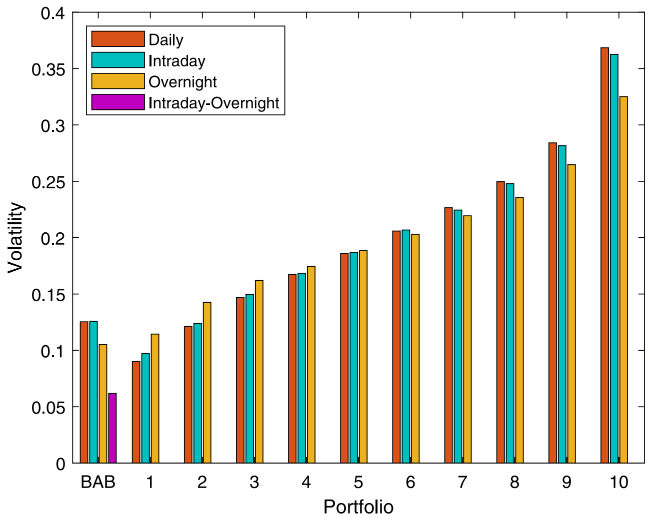

Fig. 4. Annualized volatility. We evaluate the annualized volatility of daily, intraday, and overnight BAB factors, the difference between the intraday and overnight BAB returns and ten beta-sorted portfolios related to each trading period. Portfolio one (ten) contains stocks with low (high) beta values.

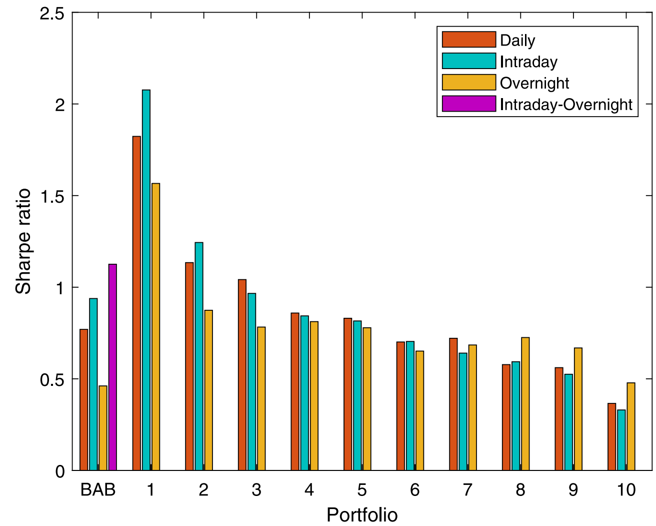

Fig. 5. Annualized Sharpe ratio. Annualized Sharpe ratio of daily, intraday, and overnight BAB factors, the difference between the intraday and overnight BAB returns, and ten beta-sorted portfolios for each trading period.

relationship (i.e., high book-to-market securities affect the BAB portfolio returns). Finally, the momentum coefficient in the four-factor model is statistically significant and shows a positive relationship for all portfolios.

3.1. Beta portfolios

Using the stock's market risk exposure (i.e., beta) as a signal for portfolio sorting is a common practice in empirical financial research. This approach allows us to investigate the relationship between the returns and beta during market opening and closure.

For each trading period, we construct ten unweighted portfolios. At the end of each calendar month, we sort and divide stocks according to the daily, intraday, and overnight pre-ranking beta values. Portfolio one (ten) contains stocks with low (high) beta values. As we can see in Appendix B Table B.3, each portfolio includes about 369 stocks per month, and the annualized average returns are very similar. As in Frazzini and Pedersen (2014), we find that the annualized Sharpe ratio decreases in high beta portfolios (Fig. 5) and, at the same time, volatility increases with beta (Fig. 4). This behavior is present in both the daily and intraday portfolios. Instead, looking at overnight portfolios, we observe lower returns, and the volatility does not decrease with beta. The portfolios with low beta values seem more profitable, especially using the intraday signal. Indeed, they have lower volatility and, at the same time, a higher Sharpe ratio.

Considering the excess returns of the ten portfolios, we evaluate alpha using simple regression methods (i.e., a CAPM, a three-factor model, and a four-factor model). As we can see in Appendix B Table B.4, we find positive and statistically significant alphas (implying abnormal portfolio returns) in almost all regressions. A nearly vanishing alpha characterizes high beta portfolios, i.e., they are more volatile and less profitable.

Indeed, considering the CAPM alpha coefficient of the daily and intraday portfolios, we observe that it decreases at increasing beta values (Fig. 6). This finding is consistent with the results of Frazzini and Pedersen (2014). As we can notice, we do not see this relationship in the overnight portfolios where the alpha of high beta portfolios is constant.

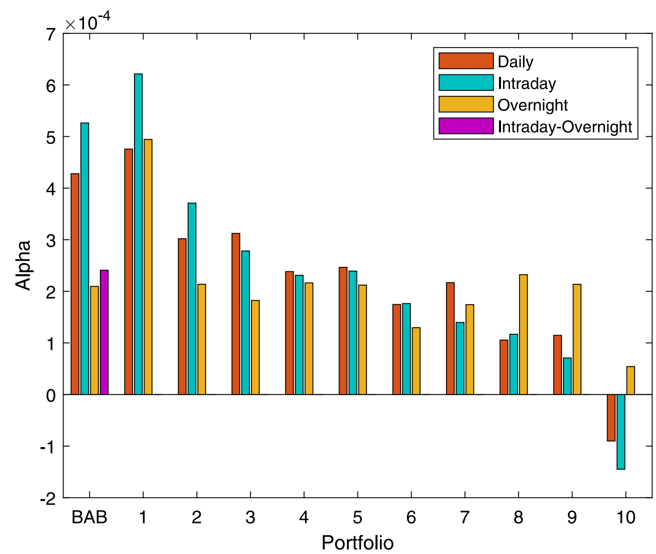

Fig. 6. CAPM alpha. Considering the values of daily, intraday, and overnight pre-ranking betas, for each trading period, we organize a BAB portfolio and ten beta-sorted portfolios (portfolio one contains stocks with the lowest beta, portfolio ten those with the highest). We evaluate alpha by regressing daily excess returns on excess market return, i.e., the classical CAPM.

3.2. The impact of nano and micro-caps on the BAB strategy

Considering the market capitalization of the stocks involved in the strategy (Appendix B, Fig. B.1), we note how portfolios are predominantly composed of nano, micro, and small stocks.[5] As well known from the literature, those stocks are riskier and outperform large stocks.

To quantify the effect on the cumulative BAB returns of the smallest stocks, we discard from our analysis all stocks smaller than the 5th

[5] Considering the stock's value we can classify securities as: nano-caps value less than 50M; micro-caps values between 50M and 300M; small-caps values between 300M and 2B; mid-caps values between 2B and 10B; big-caps values between 10B and 200B; mega-caps values greater than 200B.

Table 4
Main statistics on BAB returns. Values of annualized returns, annualized volatility, and Sharpe ratio of the BAB returns on three portfolios: daily, intraday, overnight, and the difference between the intraday and overnight BAB returns. We consider all the stocks with a market capitalization greater than 5th percentile breakpoints of the NYSE ME.

BAB Returns				
	BAB^d	BAB^{id}	BAB^{ov}	$BAB^{id} - BAB^{ov}$
Num. of stocks	2517	2517	2517	2517
Returns	0.0456	0.0489	0.0367	0.0121
Volatility	0.1244	0.1197	0.1056	0.0525
Sharpe	0.3668	0.4083	0.3476	0.2311

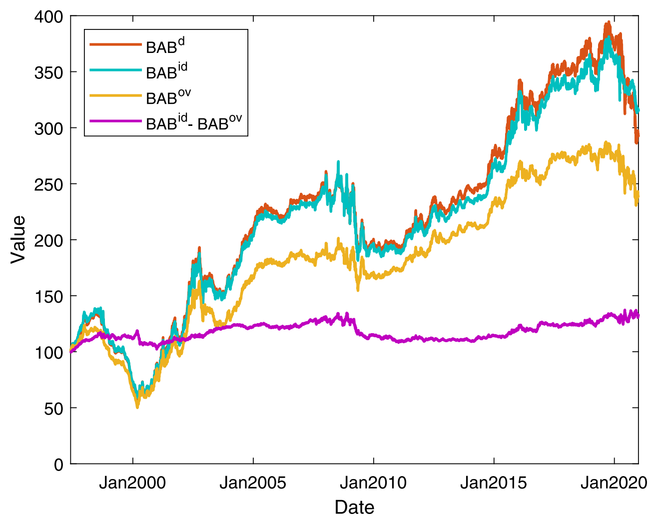

Fig. 7. Cumulative BAB portfolio returns. We evaluate the cumulative values of the daily, intraday, and overnight BAB factors and the difference between the intraday and overnight BAB returns. We consider all the stocks with a market capitalization greater than 5th percentile breakpoints of the NYSE ME.

percentile breakpoints of the NYSE market equity, adopting the ME breakpoints of Kenneth French's database. [6]

In this way, we exclude 2487 stocks, mostly belonging to the nano and micro-caps category (Appendix B, Fig. B.1). Evaluating the BAB strategy on the remaining 8597 stocks, we have, on average, 2517 stocks per month, 1258 that go long, and 1258 that go short. We get positive returns from all strategies (Table 4), but, in this case, we do not find a portfolio that performs sharply better than the others (Fig. 7). Also the difference between the intraday and the overnight BAB portfolio performances is less noticeable, leading to lower profitability for the portfolio obtained by taking the difference between intraday and overnight BAB returns (Table 4). Furthermore, the Sharpe ratios are not statistically different (Appendix B, Table B.2).

4. Conclusions

Many empirical studies highlight how the market closure affects open prices, leading to differences between the values of returns, volatility, and beta that are computed during the trading (open-to-close) and the non-trading (close-to-open) period. We exploit the different behavior of daily, intraday, and overnight betas in the context of Frazzini and Pedersen (2014) BAB strategy. The BAB strategy constructs a portfolio using the beta value as a signal. In particular, they create a factor that goes long on low beta stocks and short on high beta ones. Using this approach, they take advantage of a CAPM anomaly that was noticed and highlighted by Black (1993): the security market line is flatter than the theoretical one.

Starting from the Frazzini and Pedersen (2014) approach, we construct three BAB portfolios where stocks are ranked and splitted considering daily, intraday, and overnight beta values. In particular, at the beginning of each month, we compute the value of the pre-ranking betas, allocate the stocks, and assign the weights to the long and short portfolios. Analyzing the US stocks between June 2, 1997, and December 31, 2020, we observe how signal choice and portfolio construction influence the BAB returns. Indeed, although the three portfolios show the same level of risk, i.e., similar values for volatility, we find that the intraday strategy provides higher returns and Sharpe ratio. Furthermore, considering the high correlation between the intraday and overnight BAB portfolios, we decided to combine them into a simple long-short portfolio, buying the intraday and selling the overnight BAB portfolio. In this way, we obtain a profitable leverage strategy lowering the risk and increasing the Sharpe ratio.

Differently from the trading strategies of Lou et al. (2019), which give higher returns overnight, the BAB strategy is more profitable intraday. This finding is consistent with the work of Hendershott et al. (2020), in which they show the validity of the CAPM overnight. They construct a profitable BAB strategy similar to Frazzini and Pedersen (2014), suggesting betting against beta intraday and betting on beta overnight. Although they change the original strategy, they confirm higher returns during the trading period.

As already observed by Novy-Marx and Velikov (2022), the BAB strategy appears to be influenced by the size of the stocks. Although Frazzini and Pedersen (2014) do not consider the firm size in portfolio construction, Novy-Marx and Velikov (2022) observe how the BAB strategy over-weights the smallest stocks, thus leading to a high strategy cost. Looking at the market capitalization of the long and short portfolios at portfolio formation (Fig. 3), we observe that the most profitable portfolios, i.e., the daily and the intraday ones, have a size that is higher for long than for short positions. This result suggests that stocks with a high market capitalization are more profitable for this strategy. These findings are confirmed by our evaluation of factor models, i.e., CAPM, Fama and French three and four-factor models. Indeed, all these regressions assign a negative value to the SMB factor. On the other hand, looking at the market capitalization of the stocks included in the analysis, we observe how the dataset is unbalanced towards micro, nano, and small securities. As is well known from the literature, those stocks are riskier and sometimes more profitable than the large ones. To check the robustness of our findings and BAB performance, we redo the BAB portfolios analysis discarding the stocks with a market capitalization smaller than the 5th percentile breakpoints of the NYSE ME. Although all strategies remain profitable, contrary to the previous results, the daily, intraday, and overnight BAB portfolios show similar values. We can therefore conclude that the outstanding performance of the intraday BAB strategy was due to the high returns of micro-caps during the trading time.

Considering beta as a signal for portfolio construction is very common in the literature. For this reason, we construct ten unweighted portfolios according to the values of the daily, intraday, and overnight pre-ranking betas at the end of each month. Portfolio one (ten) contains low (high) beta stocks. We find that the Sharpe ratio and volatility, respectively, decrease and increase with the beta, independently of the trading period (i.e., high beta stocks are risky and less profitable). Moreover, we find abnormal returns from almost all portfolios by implementing the factor models on these portfolios. In the intraday and overnight portfolios set we find that alpha decreases in high beta portfolios. This behavior does not appear in portfolios sorted using overnight beta values. These show positive alpha for all the portfolios without a specific beta-dependent pattern.

[6] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_me_breakpoints.html.

Looking at the size of these beta-sorted portfolios, we observe how, in this analysis, we cannot establish a clear relationship between beta, size, and returns. The more and less profitable portfolios, i.e., 1 and 10, have a low capitalization on average (in particular, the daily and intraday ones). In this case, profitability seems more related to beta than to size. Only overnight beta-sorted portfolios show a positive relationship between beta and size but without identifying any particular pattern of returns.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Robustness of pre-ranking beta evaluation

The methodology used for the pre-ranking beta evaluation involves the computation of correlations and volatilities on a five- and one-year rolling window, respectively. This approach discards those securities showing less than 750 observations for correlations and 120 for volatilities, implying the exclusion of 4980 stocks over the 16 149 of the whole dataset. This choice allows us to faithfully compare our strategy with that of Frazzini and Pedersen (2014). On the other hand, this could lead to a bias selection problem. For this reason and to test the robustness of our results, we decide to evaluate pre-ranking beta and the returns of the BAB strategy varying the two rolling window time horizons. In one case, we consider a three-year (six-month) rolling window for correlations (volatilities), employing securities with more than 375 (60) observations. In another case, we use a one-year (three-month) rolling window for correlation (volatilities), keeping in the analysis those securities with more than 120 (30) observations.

Choosing smaller rolling windows for correlation and volatility calculations led to higher variability in the pre-ranking betas and, thus, in the composition of the portfolios constructed by the strategy. In both cases, we can include more stock in the evaluation, i.e., the nan tolerance in the stock choice is less restrictive (Table A.1). As we can see in Table A.2, reducing the size of the rolling windows does not affect our results: the intraday strategy is always the most profitable. In fact, it shows a higher Sharpe ratio which is statistically different from the daily one (Table A.3).

Table A.1
Pre-ranking beta time Horizon and Number of Stocks. We evaluate pre-ranking beta considering two different time horizons: three years (one year) for correlation and six months (three months) for volatility. Changing the time horizon leads to different restrictions for stock selections. We show the total and monthly average number of stocks used in each strategy.

Time Horizon and Number of Stocks			
Time Horizon (corr/vol)	5y/1y	3y/6 m	1y/3 m
NaN tol. (corr/vol)	750/120	375/60	120/30
Total number of stocks	11 084	13 696	15 328
Monthly num. of stocks	3693	4196	4595

Table A.2
Main statistics on BAB returns using different time horizons for the pre-ranking beta. We show the values of annualized returns, annualized volatility, and Sharpe ratio of the BAB returns on three portfolios: daily, intraday, and overnight. We construct the portfolios considering two distinct time horizons: three years (one year) for correlation and six months (three months) for volatility.

BAB Returns						
	Corr_{3y} - Vol_{6m}			Corr_{1y} - Vol_{3m}		
	BAB^d	BAB^{id}	BAB^{ov}	BAB^d	BAB^{id}	BAB^{ov}
Returns	0.0854	0.1076	0.0374	0.0783	0.0965	0.0368
Volatility	0.1345	0.1362	0.1102	0.1457	0.1462	0.1177
Sharpe	0.6348	0.7899	0.3396	0.5375	0.6603	0.3130

Table A.3
Studentized bootstrap Sharpe ratio test on BAB returns. We show the p-value of the two-sided test of equal Sharpe ratios evaluated by the studentized circular block bootstrap approach of Ledoit and Wolf (2008). We consider 4999 bootstrap replications for computing the p-value and an optimal block-length. Those returns are evaluated considering for the pre-ranking beta computation three-year for correlation and six-months for volatility (on the top), and one-year for correlation and three-months for volatility (on the bottom).

Sharpe ratio test on BAB returns			
	Sharpe	p-value	
		BAB^d	BAB^{id}
BAB^d	0.0400		
BAB^{id}	0.0497	0.0066	
BAB^{ov}	0.0214	0.0002	0.0002

Sharpe ratio test on BAB returns			
	Sharpe	p-value	
		BAB^d	BAB^{id}
BAB^d	0.0339		
BAB^{id}	0.0416	0.0400	
BAB^{ov}	0.0197	0.0002	0.0002

Appendix B. Additional tables and figures

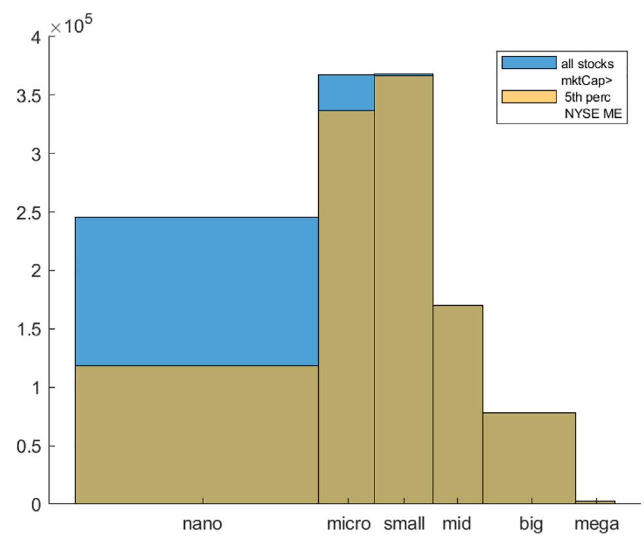

Fig. B.1. Monthly stock distribution by market capitalization. We represent the size distribution of the stocks used each month for the BAB portfolios construction. The original dataset use 10831 stocks, deleting from those all the stock with a market capitalization lower than the 5th percentile breakpoints of the NYSE ME we have 8542 stocks. Considering the stock's value we can classify securities as: nano-caps value less than 50M; micro-caps values between 50M and 300M; small-caps values between 300M and 2B; mid-caps values between 2B and 10B; big-caps values between 10B and 200B; mega-caps values greater than 200B.

Table B.1
Studentized bootstrap Sharpe ratio test on BAB returns. We show the p-value of the two-sided test of equal Sharpe ratios evaluated by the studentized circular block bootstrap approach of Ledoit and Wolf (2008). We consider 4999 bootstrap replications for computing the p-value and a optimal block-length.

Sharpe ratio test on BAB returns				
	Sharpe	p-value		
		BAB^d	BAB^{id}	BAB^{ov}
BAB^d	0.0485			
BAB^{id}	0.0591	0.0048		
BAB^{ov}	0.0290	0.0002	0.0002	
$BAB^{id} - BAB^{ov}$	0.0709	0.1744	0.4034	0.0348

Table B.2
Studentized bootstrap Sharpe ratio test on BAB returns. We show the p-value of the two-sided test of equal Sharpe ratios evaluated by the studentized circular block bootstrap approach of Ledoit and Wolf (2008). We consider 4999 bootstrap replications for computing the p-value and an optimal block-length. In this case we consider all the stocks with a market capitalization greater than the 5th percentile breakpoints of the NYSE ME.

Sharpe ratio test on BAB returns				
	Sharpe	p-value		
		BAB^d	BAB^{id}	BAB^{ov}
BAB^d	0.0231			
BAB^{id}	0.0257	0.4780		
BAB^{ov}	0.0219	0.7966	0.5288	
$BAB^{id} - BAB^{ov}$	0.0145	0.6126	0.4594	0.7114

Table B.3
Main statistics on beta portfolios. We evaluate the annualized returns, annualized volatility, and Sharpe ratio of the ten beta sorted portfolios for each trading period, computed between June 2, 1997, and December 31, 2020. Stocks are allocated into ten portfolios, considering, at the end of each calendar month, the value of daily intraday and overnight pre-ranking betas. Portfolio one contains stocks with lower betas, and portfolio ten those with higher betas.

Daily portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	369.52	369.59	369.52	369.56	369.32	369.82	369.50	369.58	369.50	369.61
Mkt Cap.	1.70E+09	5.49E+09	5.62E+09	5.73E+09	5.94E+09	5.76E+09	5.29E+09	4.80E+09	4.31E+09	2.83E+09
Returns	0.1642	0.1375	0.1529	0.1439	0.1544	0.1443	0.1634	0.1442	0.1594	0.1348
Volatility	0.0901	0.1212	0.1468	0.1675	0.1859	0.2059	0.2265	0.2497	0.2841	0.3685
Sharpe	1.8231	1.1342	1.0416	0.8591	0.8305	0.7011	0.7213	0.5776	0.5610	0.3659
Intraday portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	369.52	369.59	369.52	369.56	369.32	369.82	369.50	369.58	369.50	369.61
Mkt Cap.	6.62E+08	5.12E+09	5.93E+09	5.91E+09	6.70E+09	5.96E+09	5.41E+09	4.68E+09	4.07E+09	2.92E+09
Returns	0.2018	0.1541	0.1446	0.1421	0.1526	0.1456	0.1438	0.1470	0.1478	0.1197
Volatility	0.0972	0.1239	0.1497	0.1684	0.1871	0.2068	0.2245	0.2478	0.2816	0.3626
Sharpe	2.0765	1.2440	0.9661	0.8435	0.8158	0.7039	0.6404	0.5933	0.5250	0.3300
Overnight portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	369.52	369.59	369.52	369.56	369.32	369.82	369.50	369.58	369.50	369.61
Mkt Cap.	3.98E+08	1.85E+09	4.06E+09	4.71E+09	5.38E+09	5.55E+09	5.98E+09	6.55E+09	6.65E+09	6.23E+09
Returns	0.1793	0.1247	0.1267	0.1418	0.1467	0.1323	0.1502	0.1709	0.1770	0.1554
Volatility	0.1145	0.1427	0.1620	0.1746	0.1884	0.2030	0.2194	0.2356	0.2648	0.3251
Sharpe	1.5663	0.8741	0.7825	0.8122	0.7788	0.6514	0.6847	0.7254	0.6684	0.4780

Table B.4
Factor models on beta portfolio returns. Considering the values of daily, intraday, and overnight pre-ranking betas, we organize for each trading period ten betas sorted portfolios. Portfolios are unweighted and are updated each month. Portfolio one contains stocks with lower beta, while portfolio ten allocates those with a higher beta. We evaluate alpha and beta by regressing daily excess returns on different factors. First, we consider as an explanatory variable the excess market return, i.e., the classical CAPM. Then Fama and French's (1992) three-factor model, where the factors are excess market return (Mkt), value (SMB), and book to market (HML). And finally, we evaluate a four-factor model adding to the previous regressors the daily factor related to momentum (MOM). In parenthesis, below the coefficient estimates, we display t-statistics. We represent in bold the values with a 5% statistical significance. For all the evaluations, we consider US stocks between June 2, 1997, and December 31, 2020.

Daily portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**4.76E−04**	**3.02E−04**	**3.12E−04**	**2.38E−04**	**2.47E−04**	**1.75E−04**	**2.17E−04**	1.06E−04	1.15E−04	−9.01E−05
	(8.38)	(5.02)	(5.01)	(3.66)	(3.65)	(2.36)	(2.70)	(1.18)	(1.09)	(−0.58)
CAPM β	**0.2888**	**0.4839**	**0.6304**	**0.7401**	**0.8367**	**0.9289**	**1.0248**	**1.1264**	**1.2732**	**1.5823**
	(63.86)	(100.88)	(127.06)	(142.65)	(155.57)	(157.63)	(159.90)	(157.49)	(152.48)	(127.05)
Three-Factor α	**4.64E−04**	**2.82E−04**	**2.87E−04**	**2.08E−04**	**2.14E−04**	**1.38E−04**	**1.75E−04**	5.89E−05	5.97E−05	−1.59E−04
	(8.73)	(5.53)	(6.08)	(4.75)	(5.10)	(3.26)	(4.07)	(1.24)	(1.00)	(−1.38)
Four-Factor α	**4.53E−04**	**2.65E−04**	**2.72E−04**	**1.99E−04**	**2.13E−04**	**1.45E−04**	**1.95E−04**	**9.88E−05**	**1.28E−04**	−2.88E−06
	(8.55)	(5.25)	(5.82)	(4.55)	(5.09)	(3.46)	(4.64)	(2.24)	(2.47)	(−0.03)
Intraday portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**6.21E−04**	**3.71E−04**	**2.78E−04**	**2.31E−04**	**2.39E−04**	**1.76E−04**	1.40E−04	1.17E−04	7.09E−05	−1.45E−04
	(9.89)	(5.66)	(4.22)	(3.47)	(3.45)	(2.43)	(1.81)	(1.35)	(0.69)	(−0.96)
CAPM β	**0.2991**	**0.4742**	**0.6336**	**0.7403**	**0.8372**	**0.9377**	**1.0227**	**1.1259**	**1.2675**	**1.5669**
	(63.86)	(100.88)	(127.06)	(142.65)	(155.57)	(157.63)	(159.9)0	(157.49)	(152.48)	(127.05)
Three-Factor α	**6.07E−04**	**3.51E−04**	**2.52E−04**	**2.01E−04**	**2.05E−04**	**1.40E−04**	**9.98E−05**	7.15E−05	1.62E−05	−2.13E−04
	(10.46)	(6.35)	(5.10)	(4.45)	(4.95)	(3.38)	(2.42)	(1.57)	(0.28)	(−1.91)
Four-Factor α	**6.02E−04**	**3.40E−04**	**2.41E−04**	**1.93E−04**	**2.05E−04**	**1.49E−04**	**1.18E−04**	1.08E−04	8.22E−05	−6.97E−05
	(10.38)	(6.17)	(4.90)	(4.29)	(4.93)	(3.61)	(2.91)	(2.53)	(1.65)	(−0.75)
Overnight portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**4.94E−04**	**2.14E−04**	**1.82E−04**	**2.16E−04**	**2.12E−04**	1.29E−04	**1.74E−04**	**2.32E−04**	**2.14E−04**	5.41E−05
	(7.48)	(3.25)	(2.76)	(3.31)	(3.10)	(1.81)	(2.28)	(2.78)	(2.21)	(0.40)
CAPM β	**0.4074**	**0.5918**	**0.7054**	**0.7796**	**0.8483**	**0.9205**	**0.9968**	**1.0662**	**1.1898**	**1.4023**
	(77.35)	(112.86)	(134.20)	(149.69)	(155.86)	(161.86)	(163.74)	(160.17)	(154.41)	(129.26)
Three-Factor α	**4.75E−04**	**1.88E−04**	**1.52E−04**	**1.85E−04**	**1.77E−04**	**9.26E−05**	**1.35E−04**	**1.88E−04**	**1.64E−04**	−2.37E−06
	(8.03)	(3.65)	(3.37)	(4.47)	(4.48)	(2.34)	(3.29)	(4.29)	(2.96)	(−0.02)
Four-Factor α	**4.70E−04**	**1.82E−04**	**1.48E−04**	**1.83E−04**	**1.77E−04**	**1.03E−04**	**1.55E−04**	**2.22E−04**	**2.20E−04**	1.32E−04
	(7.94)	(3.54)	(3.28)	(4.42)	(4.48)	(2.62)	(3.89)	(5.38)	(4.45)	(1.58)

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