



## Quantitative Asset Management Final Project

Replication of "Betting Against Beta"

***Group Member:***

Niko Hiananto  
Tingting Zhou  
Yuting Shan  
Luhang Fang  
Yingxin Wang

## Contents

1. Background .....	2
2. Main methodology .....	2
3. Implementation of BAB Strategy .....	3
4. Conclusions from Implementation: .....	7
5. Appendix .....	9
Data and methodology .....	9
Estimating betas .....	9
Results from using monthly data from CRSP .....	11

## I. Background

In Hou, Xue and Zhang (2020), they conducted a gigantic replication of 447 anomalies and made a conclusion that 286 (64%) out of these anomalies are insignificant at the 5% confidence level. Most of these anomalies are traded on well-known factors, including momentum, value-versus-growth, investment, profitability, intangibles and trading frictions. Excess returns decrease and even disappear as more investors are attracted to the market. We think that a good strategy should be practically replicated, generate robust returns, yield relatively high risk-adjusted returns and match closely with the investment constraints in reality. Betting against Beta strategies meet the above standards as follows.

(1). Frazzini, and Pedersen (2014), we replicated the BAB strategy from 1926 to 2012, the anomaly is still significant. Moreover, we implemented BAB strategy in sub-sample periods from 2007 to 2019 and 2015 to 2019, both generated significant results. Compared to the results in Hou, Xue and Zhang (2020), BAB anomaly works well.

(2). The BAB strategy generated an average excess monthly return 0.7% during 1926 to 2012, 0.7% from 2007 to 2019, and even 1% during recent years between 2015 to 2019. The returns have strong robustness.

(3). Compared to the robust return, the corresponding annualized volatility of three sample periods are 11.2%, 9.5% and 8.6%, which are much lower than the market index volatility 15%-16%, indicating a higher risk adjusted return from BAB strategy.

(4). In the real world, some investors are prohibited from using leverage, and other investors' leverage is limited by margin requirements. Those investment constraints lead to the overvaluation of high beta assets. Therefore, investors not limited in leverage (arbitrageurs) could exploit this inefficiency by BAB strategies. The assumptions based on constraints of leverage and margins are in accord with the real world.

To conclude, we think that BAB strategy is worthwhile to be recommended to investors.

## II. Main methodology

Following Frazzini, and Pedersen (2014), we focus on examining the betting against beta factors in the US stock market. Our US equity data include all available common stocks on CRSP between January 1926 and December 2019. All returns are in US dollars, and excess returns are above the 30-day US Treasury bill rate.

We measure betas by combining market correlations estimated using five years of overlapping three-day returns with volatilities estimated using one year of daily data.

$$\hat{\beta}_i = \hat{\rho} \frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

we will also shrink the final beta estimates for all the betas across all assets and time using the following formula:

$$\hat{\beta}_{shrunked,i} = w_i \hat{\beta}_i + (1 - w_i) \hat{\beta}^{XS}$$

At the beginning of each calendar month, stocks are ranked in ascending order on the basis of their estimated betas at the end of the previous month. The ranked stocks are assigned to one of ten deciles portfolios based on NYSE breakpoints. All stocks are equally weighted within a given portfolio, and the portfolios are rebalanced every month to maintain equal weights.

To construct the betting against beta factor, all stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas, and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of one at portfolio formation. The betting against beta factor is a self-financing portfolio that is long the low-beta portfolio and short the high-beta portfolio (The replication procedures and notations are attached in Appendix). The monthly BAB factor return is calculated as below:

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

### III. Implementation of BAB Strategy

We implemented the BAB strategy in three sample periods, (1) 1926 to 2015, replicate the original paper, (2) 2007 to 2019, evaluate its performance through the financial crisis to present, (3) 2015 to 2019, to test its effectiveness in recent years.

For the sample period from 1926 to 2012, as the table shows that the BAB strategy has generated an average monthly excess return as 0.7% with a noticeable lower volatility, and the Sharpe ratio is the highest among all. The reasons that our replicating table looks slightly different from the table in the paper may be: (1) Our stock data did not contain liquidity risks. (2) We filtered common shares, but we did not limit exchange code as it was not specified in the original paper. (3) We did not include the delisting return as the paper did not specify how the delisting return was calculated.

Table 1: 1926-2012

Excess return (monthly return, in percentage), volatility and sharpe ratio are annualized

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess Return	0.84	0.94	0.94	1.00	1.00	1.02	1.06	1.03	1.02	0.84	0.70
volatility	17.0	19.4	21.9	23.5	24.4	27.8	28.3	30.4	33.5	40.6	11.2
SR	0.59	0.58	0.52	0.51	0.49	0.44	0.45	0.41	0.37	0.25	0.75
SK(m)	1.27	0.84	0.60	0.93	0.50	1.73	1.08	1.42	1.16	1.47	-0.39

When testing the strategy's performance in terms of exposures to other risk factors, such as MKT, SMB, HML, RMW, CMA, low beta portfolios always have higher positive alpha while high beta portfolios have negative alphas. We also regress BAB on those risk factors. The BAB factor shows significant t-statistics (3.20) (5% confidence level) for all the five Fama French factors. BAB factor has positive alpha which cannot be explained by other risk factors.

Table 2: 1926-2012

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Three-factor alpha	<b>0.35</b>	<b>0.30</b>	<b>0.27</b>	<b>0.17</b>	<b>0.14</b>	<b>0.06</b>	<b>-0.02</b>	<b>-0.04</b>	<b>-0.12</b>	<b>-0.54</b>	<b>0.69</b>
t-value	4.41	4.51	4.12	2.63	2.29	0.94	-0.25	-0.55	-1.17	-3.13	4.99
Four-factor alpha	<b>0.35</b>	<b>0.25</b>	<b>0.23</b>	<b>0.14</b>	<b>0.11</b>	<b>0.03</b>	<b>-0.04</b>	<b>-0.04</b>	<b>-0.06</b>	<b>-0.31</b>	<b>0.52</b>
t-value	4.35	3.81	3.49	2.13	1.73	0.42	-0.58	-0.56	-0.59	-1.85	3.86
Five-factor alpha	<b>0.33</b>	<b>0.21</b>	<b>0.19</b>	<b>0.10</b>	<b>0.07</b>	<b>0.01</b>	<b>-0.04</b>	<b>-0.04</b>	<b>-0.01</b>	<b>-0.21</b>	<b>0.43</b>
t-value	3.99	3.13	2.84	1.49	1.19	0.15	-0.52	-0.52	-0.12	-1.27	3.20
Beta(realized)	0.67	0.85	0.95	1.03	1.10	1.17	1.24	1.34	1.47	1.72	-0.10

For the second sample period from 2007 to 2019. The table below shows a very similar result compared to Table 1, which proves that the BAB strategy generates robust returns during the sub-sample period. Similarly, the BAB factor still generates positive alpha with significant t-statistics (3.21) when regressed on the five factor variables.

Table 3: 2007-2019

Excess return (monthly return, in percentage), volatility and sharpe ratio are annualized

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess Return	0.77	0.83	0.88	0.94	0.75	0.84	0.80	0.98	0.79	0.48	0.70
volatility	12.0	14.3	16.1	17.5	18.8	20.5	21.9	24.6	26.8	34.9	9.5
SR	0.77	0.7	0.66	0.64	0.48	0.49	0.44	0.48	0.35	0.17	0.88
SK(m)	-1.04	-0.66	-0.5	-0.42	-0.46	-0.22	-0.07	0.29	0.19	0.59	-0.44

Table 4: 2007-2019

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Three-factor alpha	<b>0.30</b>	<b>0.23</b>	<b>0.20</b>	<b>0.20</b>	<b>-0.04</b>	<b>0.01</b>	<b>-0.06</b>	<b>0.07</b>	<b>-0.24</b>	<b>-0.62</b>	<b>0.64</b>
t-value	2.30	2.09	2.03	2.27	-0.51	0.08	-0.57	0.52	-1.41	-1.88	3.20
Four-factor alpha	<b>0.38</b>	<b>0.28</b>	<b>0.22</b>	<b>0.27</b>	<b>-0.01</b>	<b>0.08</b>	<b>-0.02</b>	<b>0.09</b>	<b>-0.17</b>	<b>-0.43</b>	<b>0.67</b>
t-value	2.92	2.50	2.19	3.05	-0.07	0.82	-0.20	0.61	-0.98	-1.28	3.25
Five-factor alpha	<b>0.38</b>	<b>0.28</b>	<b>0.22</b>	<b>0.27</b>	<b>0.00</b>	<b>0.10</b>	<b>-0.01</b>	<b>0.10</b>	<b>-0.17</b>	<b>-0.44</b>	<b>0.66</b>
t-value	2.89	2.51	2.18	3.12	0.00	0.99	-0.11	0.67	-0.98	-1.30	3.21
Beta(realized)	0.72	0.91	1.05	1.15	1.24	1.33	1.41	1.55	1.70	2.01	-0.07

In the final step, we test its performance in the US equity market from 2015 to 2019. The cumulative monthly returns of ten deciles of portfolios and BAB factor are shown below, the low beta deciles portfolios kept outperforming the high beta deciles portfolios during the sample period.

Figure 1: 2015-2019

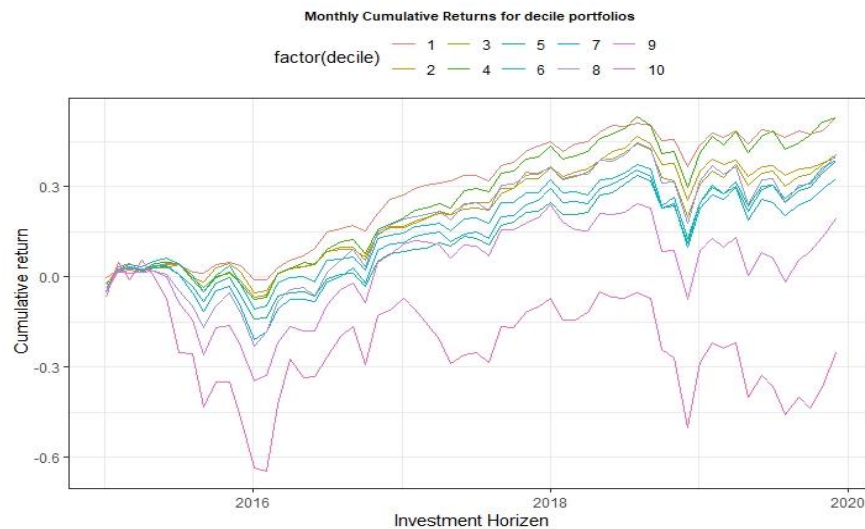
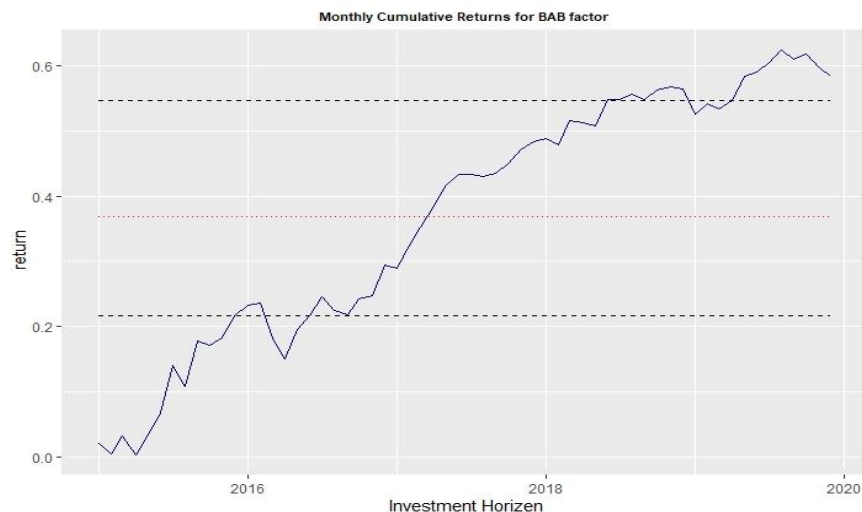


Figure 2: 2015-2019



Again, the BAB factor delivers the highest Sharpe Ratio and lowest volatility of returns. The result also shows that low beta portfolios have higher positive alphas while high beta portfolios have negative alphas during this sample period. The anomaly of BAB factor is still significant and even yields a higher average monthly return in recent 5 years.

Table 5: 2015-2019

Excess return (monthly return, in percentage), volatility and sharpe ratio are annualized

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess Return	0.84	0.65	0.67	0.89	0.66	0.68	0.60	0.76	0.45	-0.06	1.00
volatility	9.6	12.1	13.6	14.7	15.7	16.6	17.7	19.9	22.5	32.7	8.6
SR	1.05	0.64	0.59	0.73	0.50	0.49	0.41	0.46	0.24	-0.02	1.40
SK(m)	-0.54	-0.63	-0.37	-0.35	-0.11	-0.30	-0.34	-0.20	-0.07	0.24	0.12

Table 6: 2015-2019

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Three-factor alpha	<b>0.47</b>	<b>0.09</b>	<b>0.04</b>	<b>0.20</b>	<b>-0.04</b>	<b>-0.06</b>	<b>-0.20</b>	<b>0.00</b>	<b>-0.46</b>	<b>-1.07</b>	<b>1.05</b>
t-value	2.84	0.55	0.32	1.48	-0.37	-0.49	-1.64	-0.02	-1.98	-1.73	3.29
Four-factor alpha	<b>0.43</b>	<b>0.05</b>	<b>0.00</b>	<b>0.21</b>	<b>-0.07</b>	<b>-0.07</b>	<b>-0.22</b>	<b>-0.01</b>	<b>-0.45</b>	<b>-0.94</b>	<b>0.96</b>
t-value	2.61	0.30	-0.03	1.49	-0.59	-0.55	-1.71	-0.04	-1.90	-1.51	3.04
Five-factor alpha	<b>0.42</b>	<b>0.05</b>	<b>0.00</b>	<b>0.21</b>	<b>-0.07</b>	<b>-0.07</b>	<b>-0.22</b>	<b>-0.01</b>	<b>-0.46</b>	<b>-0.96</b>	<b>0.97</b>
t-value	2.58	0.30	-0.01	1.50	-0.57	-0.55	-1.76	-0.05	-2.03	-1.58	3.09
Beta(realized)	0.63	0.86	0.98	1.06	1.14	1.20	1.29	1.38	1.58	2.00	-0.17

## IV. Conclusions from Implementation:

(1). BAB factor is not a mispricing and difficult to trade away.

The BAB factor consists of a self-financing long-short portfolio of low and high beta portfolios, respectively. The long (short) portfolio has been leveraged (de-leveraged) to a beta of one and is market neutral. Under this model, the expected return of the BAB factor is positive, and the size of the expected return depends on the size of the spread of the betas and the tightness of agent's portfolio constraints. Hence, the strategy does not revolve around a mispricing, rather, a competitive equilibrium where some of the agents face leverage constraints or margin requirements. Given this economic underlying, the strategy is unlikely to be arbitrated away.

(2). BAB factor is not compensation for risk but for leverage

The strategy is not a compensation for risk, rather, it is a compensation for having access to leverage. As we replicated Frazzini and Pedersen (2014), under the replication period 1926 - 2012, we can see that the BAB factor still has significant alphas when regressed on all Fama French three factors, four factors and five factors. The anomaly is not yielded by excess risk exposure to investment and profitability or market capitalization. The strategy also actually has the lowest volatility (11.20%) compared to the other beta decile portfolios. Note that the BAB factor also delivers negative skewness (-0.44), however, it is small enough that it would most likely not be priced as the strategy's compensation. Looking at a more recent period of 2015 - 2019, the BAB factor still has the lowest volatility (8.20%) with a skewness of 0.12. Hence, it can be concluded that the BAB factor return is not a compensation for risk.

(3). BAB strategy is robust in different sample periods.

To validate our strategy, we conduct three kinds of robustness exercises. a) we change our original stock market data to monthly frequency and repeat all the steps to compute the BAB factor. The result shows the same trends and statistical significance which verify the robustness of our result. b) we use three factors (MKT, SMB, HML), four factors (MKT, SMB, HML, RMW) and five factors (MKT, SMB, HML, RMW, CMA) to explain the portfolio return of each decile. We show the risk-adjusted returns of the BAB factor are robust to different factors and are still significant. The consistent result suggests that coincidence or data mining are unlikely explanations. c) we test our strategy in two more periods: post-financial crisis and recent five years. The result shows that our strategy is robust to different sample periods.



(4). Potential risks and costs associated with the strategy:

The performance of BAB strategy hinges on the ranking stocks by their beta estimates and long short a low beta, high beta portfolio. This procedure creates portfolios that are almost the same as equal-weighted portfolios. Therefore, we may not weight stocks in proportion to their market capitalizations as is standard in asset pricing. As a result, the strategy overweighs micro-cap and nano-cap stocks and the strategy has been criticized to have achieved a high Sharpe Ratio and significant alpha due to this overweighting. Every month when we rebalance our portfolio, we need to rank betas of all firms in the market, and BAB factor requires us to trade a large amount of stocks, which could trigger high transaction costs and cut down the strategy's performance.

The BAB factor also hedges their constructed portfolios by leveraging and deleveraging the portfolios using the respective portfolios' estimated betas. By doing so, the hedge created through leveraging is actually more similar to an equal-weighted portfolio hedge than when the BAB is hedged using the value-weighted market. Hedging with equal-weighted portfolios instead of value-weighted portfolios have been attributed to significant contribution to the BAB's performance Novy-Marx and Velikov (2018). Thus, the leveraging procedure has also been criticized to have been the main compensation for the strategy's performance through a backdoor of equal-weighted portfolio hedge instead of the standard value-weighted market hedge.

Considering the implications of funding constraints for cross-sectional and time series asset returns, worsening funding liquidity should lead to losses for the BAB factor in the time series and increased funding liquidity risk compresses betas in the cross section of securities toward one.

## V. Appendix

### Data and methodology

#### 1. Universe of data

From the procedure aligned in the paper Betting Against Beta (2013), which (a) constructed beta decile portfolios and BAB factor for equity market by using all available common stocks on CRSP, (b) calculated betas with respect to the CRSP value-weighted market index, and (c) calculated excess returns by subtracting the US Treasury bill rate, we download both daily and monthly data from CRSP and then restrict sample by share code (10 or 11) and use 30-day treasury rate as risk-free rate.

To compute alphas with respect to existing factor models, we also downloaded market factor, SMB, HML, RMW, and CMA factors from Kenneth-French's website.

#### 2. Sample period

Following the steps in the paper, we limit our sample from January 1926 to March 2012. Since our strategy requires monthly rebalance, we extract Year and Month from each date.

#### 3. Missing value imputation

There exist missing data with values equal to "-99", "-88" etc. We just convert them into NA, assuming that they are unavailable at that time. Further limit on the availability of data will be conducted when estimating betas.

### Estimating betas

#### 1. Compute volatility

To compute the volatilities, we have used a one-year rolling standard deviation of the log excess returns. For the daily data, the one-day log excess returns is used and for the monthly data, the one-month log excess returns is used. We also need that at least six months (120 days) out of the one-year has non-missing data for the daily data. And for the monthly data, we require that all 12 observations are non-missing when calculating the rolling standard deviation.

## 2. Compute correlation

When computing the correlation between the asset and the market, we have used a five-year rolling horizon to account that correlation moves slower than volatilities. For the daily data, we have also used overlapping three-day log excess returns to estimate the correlation and require at least 750 days of non-missing data. For the monthly data, we have used the monthly log excess returns and require at least 36 months of data.

## 3. Compute and shrink beta

To compute the beta of each asset we estimated the beta using the following formula

$$\hat{\beta}_i = \hat{\rho} \frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

where,  $\hat{\rho}$  is the estimated correlation as computed under step (3) and  $\hat{\sigma}_i$  and  $\hat{\sigma}_m$  are the asset return volatility and market return volatility estimates as computed under step (2). Finally, we will also shrink the final beta estimates for all the betas across all assets and time using the following formula:

$$\hat{\beta}_{shrunked,i} = w_i \hat{\beta}_i + (1 - w_i) \hat{\beta}^{xs}$$

where,  $\hat{\beta}^{xs}$  is set to 1 for all assets across time. This shrinkage is used to reduce the influence of outliers and note that the shrinkage will not affect the construction of the portfolio deciles or the BAB factor as the common shrinkage factor will not affect the ranks of the security betas.

## 4. Decile Portfolios

At the end of each month, we will construct portfolio deciles based on the rank of the lagged estimated beta for each asset. If the daily data is used, the end of the month estimate of beta will be used and if monthly data is used instead, the last month's beta estimate will be used to form the portfolio. Hence, at the end of each month, we will rank the stocks according to their lagged beta estimates and use the rank to form decile portfolios. We will use NYSE breakpoints to form the decile portfolios, thus, each decile has the same number of NYSE firms. Finally, the portfolios formed will be equally weighted and will be rebalanced monthly.

## 5. Betting Against Beta factors (BAB factors)

To construct BAB factors, we will construct portfolios that long low-beta stocks and short high-beta stocks. Every month, all stocks are ranked based on their estimated lagged beta values and low-beta portfolio will consist of stocks with beta below the median and the high-beta portfolio will consist of stocks with beta above the median value. The securities are also weighted by the ranked betas, more specifically, let  $z$  be a vector of beta ranks  $z =$

$rank(\beta_{it})$  at portfolio formation, and let  $\bar{z}$  be the average/median rank. The portfolio weights of the low-beta and high-beta portfolios are given by:

$$w_H = k(z - \bar{z})^+$$

$$w_L = k(z - \bar{z})^L$$

where,  $k$  is a normalizing constant  $k = 2/1'_n |z - \bar{z}|$  and  $x^+$  and  $x^-$  denote the positive and negative elements of the vector. Hence, by construction we have that  $1'_n w_H = 1$  and  $1'_n w_L = 1$ . When constructing the BAB factor, the portfolios are scaled to have a beta of one and thus the BAB is a zero cost zero-beta portfolio that long the low-beta portfolio and short-beta portfolio.

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

where  $r_{t+1}^L = r'_{t+1} w_L$ ,  $r_{t+1}^H = r'_{t+1} w_H$ ,  $\beta_t^L = \beta'_t w_L$ , and  $\beta_t^H = \beta'_t w_H$ .

## Results from using monthly data from CRSP

We have also replicated the paper using monthly data instead of daily data, and the resulting tables and plots of the replication strategy using monthly data with the implementations as outlined above is shown below.

Table 7: 1926-2012

Excess return (monthly return, in percentage), volatility and sharpe ratio are annualized

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess Return	0.99	0.95	1.07	1.1	1.13	1.22	1.17	1.2	1.29	1.34	0.69
volatility	15.8	18.0	21.6	23.2	24.5	27.4	28.7	31.5	34.1	39.8	10.5
SR	0.75	0.63	0.60	0.57	0.55	0.53	0.49	0.46	0.46	0.40	0.79
SK(m)	2.65	1.52	1.78	1.64	1.35	1.78	1.44	1.77	2.17	1.61	-0.04

Table 8: 1926-2012

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Three-factor alpha	<b>0.27</b>	<b>0.25</b>	<b>0.22</b>	<b>0.23</b>	<b>0.19</b>	<b>0.18</b>	<b>0.10</b>	<b>0.05</b>	<b>0.05</b>	<b>-0.19</b>	<b>0.53</b>
t-value	3.90	3.97	3.60	3.72	3.15	2.82	1.40	0.69	0.57	-1.17	4.52
Four-factor alpha	<b>0.27</b>	<b>0.20</b>	<b>0.14</b>	<b>0.16</b>	<b>0.13</b>	<b>0.14</b>	<b>0.04</b>	<b>0.06</b>	<b>0.10</b>	<b>0.06</b>	<b>0.43</b>
t-value	3.74	3.27	2.33	2.68	2.14	2.12	0.61	0.72	1.05	0.39	3.68
Five-factor alpha	<b>0.24</b>	<b>0.17</b>	<b>0.09</b>	<b>0.13</b>	<b>0.10</b>	<b>0.11</b>	<b>0.04</b>	<b>0.07</b>	<b>0.13</b>	<b>0.13</b>	<b>0.35</b>
t-value	3.33	2.67	1.62	2.14	1.62	1.74	0.62	0.85	1.39	0.86	3.00
Beta(realized)	0.64	0.77	0.89	0.95	1.04	1.11	1.19	1.27	1.39	1.65	0.19

Figure 3: 1926-2012

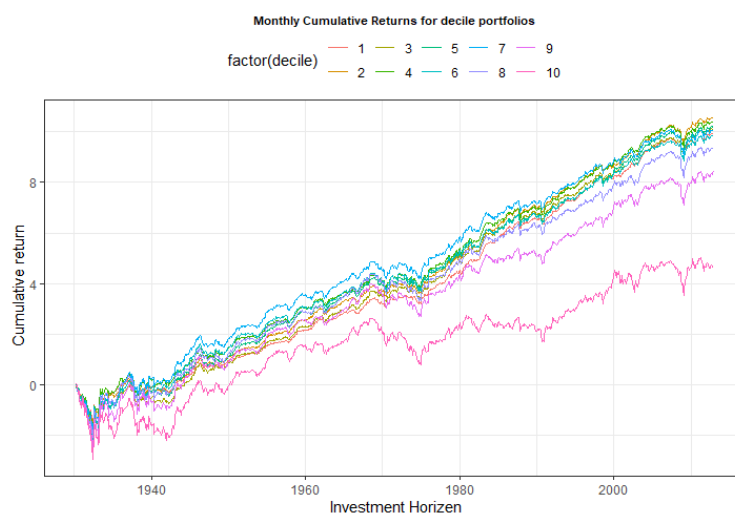


Figure 4: 1926-2012

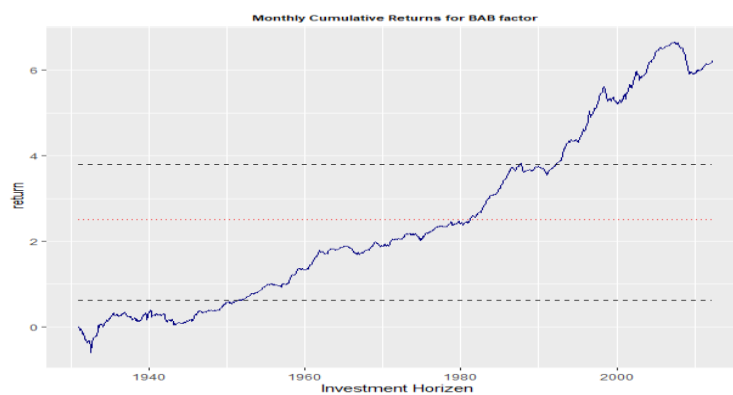


Table 9: 2007-2019

Excess return (monthly return, in percentage), volatility and sharpe ratio are annualized

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess Return	0.60	0.63	0.79	0.94	0.84	0.91	0.87	0.82	1.02	0.84	0.40
volatility	12.3	14.1	16.0	17.1	18.9	20.6	22.2	23.5	27.1	35.3	8.9
SR	0.58	0.54	0.59	0.66	0.53	0.53	0.47	0.42	0.45	0.29	0.54
SK(m)	-1.15	-0.80	-0.68	-0.51	-0.45	-0.23	-0.09	-0.26	0.35	0.97	-1.46

Table 10: 2007-2019

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Three-factor alpha	<b>0.13</b>	<b>0.06</b>	<b>0.15</b>	<b>0.29</b>	<b>0.09</b>	<b>0.13</b>	<b>0.05</b>	<b>-0.05</b>	<b>0.13</b>	<b>-0.19</b>	<b>0.15</b>
t-value	1.15	0.61	1.89	3.19	0.87	1.05	0.36	-0.33	0.59	-0.50	0.84
Four-factor alpha	<b>0.19</b>	<b>0.11</b>	<b>0.19</b>	<b>0.34</b>	<b>0.15</b>	<b>0.19</b>	<b>0.10</b>	<b>0.04</b>	<b>0.25</b>	<b>-0.05</b>	<b>0.17</b>
t-value	1.67	1.11	2.31	3.72	1.42	1.51	0.77	0.28	1.09	-0.12	0.91
Five-factor alpha	<b>0.19</b>	<b>0.10</b>	<b>0.20</b>	<b>0.34</b>	<b>0.15</b>	<b>0.21</b>	<b>0.12</b>	<b>0.07</b>	<b>0.26</b>	<b>-0.05</b>	<b>0.16</b>
t-value	1.58	1.05	2.38	3.68	1.42	1.68	0.89	0.42	1.12	-0.14	0.86
Beta(realized)	0.73	0.87	1.00	1.06	1.17	1.26	1.36	1.43	1.58	1.94	0.30

Figure 5: 2007-2019

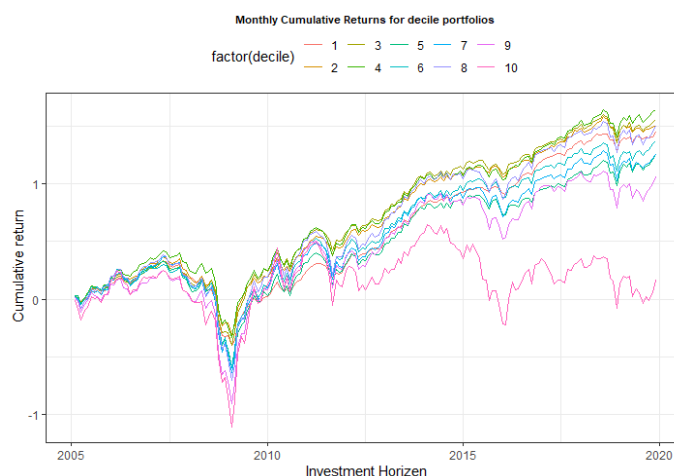


Figure 6: 2007-2019

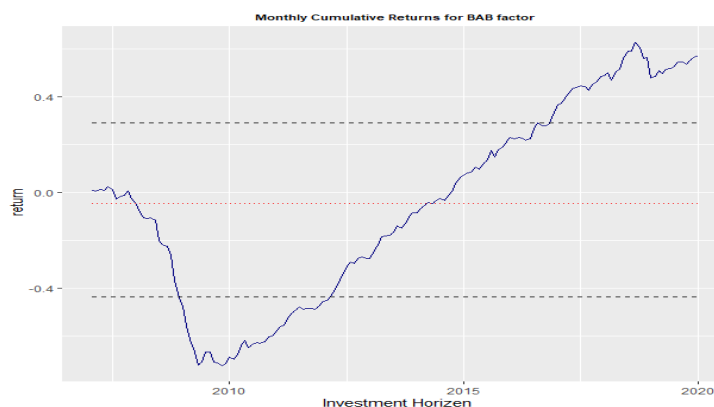


Table 11: 2015-2019

Excess return (monthly return, in percentage), volatility and sharpe ratio are annualized

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess Return	0.76	0.68	0.71	0.82	0.80	0.66	0.63	0.76	0.51	-0.03	0.86
volatility	10.1	11.7	13.7	14.2	15.0	16.3	17.7	19.2	21.9	29.5	7.6
SR	0.90	0.69	0.63	0.69	0.64	0.49	0.43	0.48	0.28	-0.01	1.36
SK(m)	-1.02	-0.56	-0.42	-0.43	-0.36	-0.44	-0.25	-0.09	-0.10	0.26	-1.28

Table 12: 2015-2019

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Three-factor alpha	<b>0.36</b>	<b>0.15</b>	<b>0.07</b>	<b>0.16</b>	<b>0.10</b>	<b>-0.12</b>	<b>-0.12</b>	<b>-0.04</b>	<b>-0.28</b>	<b>-1.03</b>	<b>0.65</b>
t-value	2.17	1.23	0.70	1.91	0.81	-0.85	-0.95	-0.18	-1.10	-1.96	2.61
Four-factor alpha	<b>0.34</b>	<b>0.12</b>	<b>0.03</b>	<b>0.12</b>	<b>0.07</b>	<b>-0.15</b>	<b>-0.11</b>	<b>-0.01</b>	<b>-0.27</b>	<b>-0.95</b>	<b>0.59</b>
t-value	2.00	0.97	0.35	1.56	0.54	-1.07	-0.87	-0.06	-1.03	-1.78	2.38
Five-factor alpha	<b>0.33</b>	<b>0.12</b>	<b>0.04</b>	<b>0.12</b>	<b>0.07</b>	<b>-0.15</b>	<b>-0.11</b>	<b>-0.01</b>	<b>-0.28</b>	<b>-0.96</b>	<b>0.59</b>
t-value	1.98	0.96	0.37	1.55	0.53	-1.05	-0.85	-0.07	-1.06	-1.87	2.36
Beta(realized)	0.67	0.82	1.00	1.05	1.10	1.20	1.27	1.35	1.48	1.88	0.28

Figure 7: 2015-2019

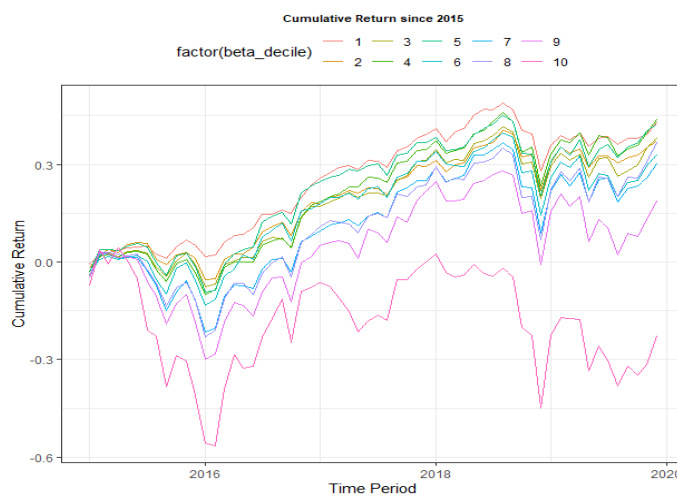


Figure 8: 2015-2019



### References

1. Andrea Frazzini and Lasse Heje Pedersen. Betting against beta. *Journal of Financial Economics*, 111(1):1-25, 2014.
2. Novy-Marx, R., & Velikov, M. (2018). Betting Against Betting Against Beta. *SSRN Electronic Journal*. doi:10.2139/ssrn.3300965