Leverage and Performance Metrics in Asset Pricing

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Abstract. Commonly used performance metrics calculated from tradable long-short strategies constructed using leverage – like Frazzini and Pedersen's (2014) Betting Against Beta and Horenstein's (2017) Betting Against Alpha – lead to specious conclusions of statistical significance. In particular, even if assets are randomly assigned to the levered strategies' long and short portfolios, too often they generate high Sharpe Ratios and statistically significant CAPM, Carhart, and Fama-French Five Factor's alphas. I call this finding *the mechanical effect of leverage on performance metrics*. I suggest various diagnostic tests to control for this effect in levered strategies.

Keywords. betting against beta, betting against alpha, factor models, leverage, Sharpe Ratio, alpha.
JEL classification. G10, G12.

1 Introduction

Since the development of the Intertemporal CAPM (Merton 1972) and the Arbitrage Pricing Theory (APT, Ross 1977), which allow for multifactor asset pricing models, the quest for risk factors other than the CAPM's market factor that can explain the cross-section of stock returns has been pervasive in the finance literature. Harvey et al. (2016) categorize 314 factors from 311 different papers published in top-tier finance journals and working papers between 1967 and 2014. The most common empirical method to create a tradable factor relies on finding a long-short strategy based on stock portfolios sorted, double sorted, and more recently triple sorted on some metrics (usually some firm characteristics, for example market capitalization and book to market value) that is not priced by other existing factors. A basic stylized fact shown in many papers to support a new variable as a factor is that portfolios sorted on certain metrics show a decreasing or increasing pattern in average excess returns. The most famous example is probably the three-factor model of Fama and French (1992), which augments the empirical CAPM with a factor capturing the size effect (SMB) and a factor capturing the value-premium (HML). Portfolios sorted on market capitalization show a decreasing pattern in average returns, and portfolios sorted on book to market value show an increasing pattern in average returns. Once these patterns are found, then some performance related metrics are calculated for the zero-net investment and dollar-neutral long-short strategy to confirm the finding of a risk factor. The most common performance metrics analyzed in the literature are the risk-premium of the factor, its Sharpe Ratio, and the significance level of the alpha (pricing error) produced by regressing the proposed factor against some popular benchmark model.[1]

The added factors to the CAPM were needed because the empirical market portfolio (henceforth Market), usually the value-weighted portfolio's excess returns over the one-month T-bill, failed to explain the cross-section of stock returns. The Market beta-return relationship known as Security Market Line (SML) was found to be too flat.[2] Recently, Frazzini and Pedersen (FP, 2014) developed a compelling theoretical explanation for the observed flat SML. In their model, some investors are constrained in the leverage they can take, which leads them to overweight their portfolio in high Market beta stocks to augment their achievable expected return. Consequently, high beta stocks are overpriced relative to low beta ones, which leads to a flat SML. This insight is further supported by the empirical findings in Christoffersen and Simutin (2017). The empirical implication of the FP model leads to a new type of factor constructed with leverage that they called Betting Against Beta (BAB). Their BAB factor is a market-neutral strategy with leverage that consists of buying a zero-net investment portfolio of low beta stocks' excess returns and selling a similar type of portfolio made of high beta stocks. Leverage is applied by using certain weights to magnify the excess return of the long portfolio and diminish the excess return of the short one.

More recently, Horenstein (2017) suggested that leverage constrained investors can bid up on any factor's betas for the same reason they bid up on the Market beta in FP. Since buying assets with a high beta corresponding to a factor other than the CAPM's Market factor is equivalent to buying an asset with a positive CAPM's alpha, he proposes a new factor called Betting Against Alpha (BAA).

[1] Barillas and Shanken (2017) show that the test assets are generally not relevant when comparing asset pricing models with tradable factors. All that is needed is to check whether a proposed new factor is priced by the already existing ones.

[2] The Capital Asset Pricing Model (CAPM) developed by Jack Treynor (1962), William Sharpe (1964), John Lintner (1965), and Jan Mossin (1966) and extended by Black (1972) predicts a positive relationship between market betas and expected returns. A puzzling finding from many empirical studies using linear factor models is that the empirical market portfolio has strong explanatory power for the comovement of stock returns, but its betas generate a flat SML. This result has been interpreted as a failure of the CAPM to explain the cross-sectional variation in expected stocks returns [Reinganum (1981), Lakonishok and Shapiro (1986), Fama and French (1992), and Fama and French (2004)]. Furthermore, the cross-sectional dispersion of the betas diminishes and becomes near constant when the CAPM is augmented with additional risk factors [e.g., Fama and French (1992) and Ahn, Perez, and Gadarowski (2013)].

This factor is further justified by other findings in the literature. For example, Barber et al. (2016) show that investors pay attention mostly to the Market factor and seem to treat other risk factors as alpha. Their finding implies that an asset with a high (low) realized beta with respect to a factor missed by the CAPM is interpreted by investors as an asset having a high (low) realized CAPM alpha. Consequently, mutual fund managers have incentives to tilt their portfolios towards assets with high non-Market betas too, since that signals superior performance to investors caring only about Market risk. Agarwal et al. (2017) obtain a similar result when analyzing hedge fund flows. Additionally, benchmarked mutual fund managers also have incentives to bid up on assets with a large index alpha, which further justifies the existence of the BAA factor.[3]

Horenstein (2017) also showed that the BAB and BAA factors work across sizes and different rebalancing periods, generating significant abnormal returns when risk is controlled by empirical factor models like the CAPM, Carhart (1997), and Fama-French Five Factor (2015) models.

Therefore, there seems to be room for a new paradigm to empirically find risk factors. If portfolios sorted on a certain metric or firm characteristic produce decreasing/increasing returns, a long-short strategy without leverage is a candidate to produce a new risk factor. If portfolios sorted on a characteristic produce flat returns, then a long-short strategy with leverage is also a candidate to produce a new risk factor. In fact, leverage applied to long-short strategies based on traded portfolios can produce positive risk premiums, whether these portfolios show decreasing, flat, or increasing patterns in excess returns. In other words, it seems that sorting portfolios on any variable might lead to finding a long-short strategy with a positive risk premium.

A major concern in the empirical finance literature is how to avoid the proliferation of factors that might not be relevant (e.g. Harvey et al. 2016 or Ahn et al. 2017). Therefore, focusing on the case of levered strategies, the goal of this paper is twofold. First, I investigate if applying leverage to a long-short strategy has non-negligible impact in Sharpe Ratios and estimated alphas. I focus on Sharpe Ratios and alphas since these two metrics are arguably the most common metrics used in the empirical asset pricing literature to measure the performance of a tradable factor. For example, given the popularity of alpha as performance metric and the pervasiveness of data mining in the literature about explaining the cross-section of stock returns, Harvey et al. (2016) suggests increasing the hurdle of an alpha's t-statistic to 3.0. Second, I investigate the performance metrics of several strategies constructed using leverage. The Market is not the only risk factor studied in the empirical finance literature. There are other traded and non-traded factors that could also be used to create levered strategies by betting against their factor loadings. Additionally, I investigate

[3]Horenstein (2017) proposes another factor with leverage as a results of the combination of the BAB factor and BAA factor called Betting Against Alpha and Beta (BAAB). The motivation for this factor is simple: If certain investors tilt their portfolio towards assets with a high realized Market beta and also towards assets with a high realized alpha, then a portfolio consisting of high realized alpha assets from the set of high realized beta ones should be the most overpriced. Horenstein (2017) showed that empirically this is the case, with the BAAB factor producing Sharpe Ratios up to three times that of the Market and larger than those of the BAB and BAA factors. I do not add the analysis of the BAAB factor to this paper since it is quite correlated with the BAA factor and does not modify any of the conclusions.

which of all the different levered strategies analyzed capture relevant information and how to use Sharpe Ratios and abnormal returns to select among the candidate levered strategies.[4]

To answer the first question, I start by simulating 100,000 strategies with leverage by randomly assigning assets to the low and high beta portfolios each year. I magnify the excess returns of the long (low) portfolio and diminish the excess returns of the short (high) portfolio using the weights from Frazzini and Pedersen's BAB strategy. From the 100,000 random strategies, I obtain an empirical distribution of their risk premiums, Sharpe Ratios and CAPM, Carhart, and FF5 alphas' t-stats. I find that that the randomly created long-short levered strategies generate positive risk premiums, high Sharpe Ratios, and alphas with t-statistics surpassing the hurdle of 3.0 suggested by Harvey et al. (2016) too often. In fact, the value 3.0 is included in the 95 percent interval of the empirical distributions of the Carhart and FF5 models' alphas t-statistics. I call this phenomena the *mechanical effect of leverage on performance metrics* (henceforth "the mechanical effect of leverage").[5]

To answer the Second question, I analyze twenty strategies constructed using leverage, in which the low and high beta portfolios are sorted on betas with respect to the five factors in FF5 and ten macroeconomic variables. Additionally, I also study the performance of the strategies proposed in Horenstein (2017) that buy assets with low CAPM, Carhart (1997), and FF5 realized alphas and sell assets with high realized alphas. The last strategies I analyze are *multifactor BAB*. In this case, the strategy consists of buying assets with low predicted expected returns and selling assets with high predicted expected returns by a multifactor model, where these returns are calculated as the factors' betas times the factors' risk premiums. I called these strategies *Betting Against Predicted Returns* (BAPR).

To compare across strategies, I develop a benchmark scenario in which I use the same weights for the long and short portfolios in every levered strategy. I use as common weights those of the Market BAB strategy. Of course, keeping the low and high portfolios' weights constant across levered strategies might not lead to the optimal outcome of individual strategies in terms of high Sharpe Ratios or large expected risk premiums. However, my goal is not to find the weights that maximize the Sharpe Ratio or the risk premium of a particular levered strategy, but to provide guidance about which strategies might contain useful information and how to use Sharpe Ratios and estimated alphas to find those relevant strategies.

Consistent with my simulation exercise, I find that almost all of the twenty strategies produce

[4]It is important to note that a reduced analysis of the second exercise is already presented in Horenstein (2017). However, the first – and most important quantitative exercise of this paper – is completely new.

[5]In the FP model, the time-varying weights used in the BAB strategy are related to the investors' funding liquidity. Therefore, what I call the mechanical effect of leverage could be related to economic fundamentals. However, what is important in this study is that, keeping constant the weights in the long-short portfolios across different levered strategies, I will be able to assess the impact of leverage in Sharpe Ratios and alphas, independently of whether the variable used to sort the strategies' portfolios is related to risk or not. This is why I call the average effect of leverage across strategies the mechanical effect of leverage.

large Sharpe Ratios and statistically significant alphas at the 1% level of significance or less.[6]

Given the previous results, and following Shanken and Barillas (2017), I analyze whether one levered strategy can be priced by another one in order to find the minimum set of levered strategies that can price all others. I find that the Market BAB strategy is not priced by any other levered strategies. Univariate regressions using the Market BAB as a dependent variable and any other levered strategy as a regressor generates statistically significant alphas at the 1% level of significance or less. On the other hand, the Market BAB strategy fails to price the BAA, BAPR, and some macroeconomic BAB strategies. Importantly, a two factor model containing the Market BAB factor and any of the BAA factors can price all other levered strategies. This is consistent with the results in Horenstein (2017), where he argues that the Market BAB and CAPM BAA factor should subsume all betting against non-Market beta strategies.

Given the results in our study, I suggest the following three diagnostic tests using Sharpe Ratios and alphas for finding relevant strategies constructed with leverage: First, a strategy's Sharpe Ratios should be large enough to rule out being a product of the mechanical effect of leverage (at least 50% larger than the Market's Sharpe Ratio). Second, Sharpe Ratios should decrease across portfolios sorted on the metric used to construct the "betting against" levered strategy. Third, a new levered strategy should produce statistically significant alphas when risk is controlled by the Market BAB and any of the BAA factors. Assessing the relevance of a levered strategy using alphas generated by models containing only levered factors lead to false positives too often.

Of course there are other methods for testing whether a new proposed factor captures relevant information missed by the already existing ones. For example, Ahn et al. (2017) and Burnside (2016) suggest using rank estimation methods. Feng et al. (2017) proposed a model selection method based on applying a double-selection LASSO in tandem with a two-pass regression. In this paper I focus on Sharpe Ratios and estimated alphas, arguably the two most common performance metrics used in the literature when analyzing tradable factors.

In a related study, Cederburg and O'Doherty (2017) explore the relevance of the Market BAB strategy and find that the alpha generated by it disappears once the estimation bias generated by the unconditional CAPM is controlled for in the conditional version of the model. Like Cederburg and O'Doherty, I am also concerned with the problems of using alpha to assess the relevance of a levered strategy and find that is not a very informative metric when common risk is controlled by a model with unlevered factors. Additionally, I also analyze the impact of leverage on Sharpe Ratios.

To sum up, this paper adds to the literature on empirical asset pricing by studying the impact of leverage on Sharpe Ratios and estimated alphas' t-statistics, and by suggesting diagnostic tests to keep these metrics relevant for comparison purposes when analyzing levered strategies.

The rest of the paper is organized as follows. Section 2 describes the data I will use and explains the construction of the levered strategies. I also provide some preliminary statistics. Section 3

[6] This is a red flag that shows the importance of having an answer to the first, and main question in this paper: How to find the relevant levered strategies using alphas and Sharpe Ratios as performance metrics?

provides the quantitative analyses. I conclude in Section 4.

2 Data and construction of the levered strategies

2.1 Data and strategies

I use monthly data on US individual stock returns from the Center for Research in Security Prices (CRSP) from January 1968 until December 2015. The returns include dividends from common stocks traded on the NYSE, NASDAQ, and AMEX, excluding REITs and ADRs. Data on the Fama-French five factors model (FF5, 2015) as well as the Momentum factor for the Carhart (1997) model are from Kenneth French's website.[7] The FF5 factors are the excess market return (Market: the return on the CRSP value-weighted portfolio minus the return on the 1-month Treasury bill), Small Minus Big (SMB), High Minus Low (HML), Robust Minus Weak (RMW), and Conservative Minus Aggressive (CMA) factors. The Carhart factors are the Market, SMB, and HML factors from FF5 plus the Momentum factor (MOM, selling losers and buying winners 6 to 12 months ago). I also use data on macroeconomic variables from the Federal Reserve Bank of St. Louis.[8] Table 1 below shows the ten macroeconomic variables used in our analysis.

[Insert Table 1 around here]

A Betting Against Beta (BAB) strategy consists of selling a portfolio containing high beta stocks' excess returns over the risk free asset and buying a portfolio of low beta stocks' excess returns, where the excess returns of the low beta portfolio are amplified while the excess returns of the high beta portfolio are reduced. I will analyze the effect of leverage on portfolios sorted using the following twenty different variables:

[Insert Table 2 around here]

Note that there are three strategies that are actually Betting Against Alpha: CAPM BAA, Carhart BAA, and FF5 BAA. Additionally, I explore the possibility of betting against multifactor betas by sorting the assets used to create portfolios on their predicted expected return by a multifactor model (i.e., factors' betas times factors' average returns) instead of a single beta. For this strategy I use portfolios sorted by predicted expected returns only for the Carhart and FF5 models (Carhart BAPR and FF5 BAPR).[9]

[7]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8]https://fred.stlouisfed.org

[9]In the case of the CAPM, as long as the expected returns of the Market factor are positive, sorting the assets based on betas or predicted expected returns is equivalent.

2.2 Construction of the levered factors

The Betting Against Beta (BAB) factor developed by Frazzini and Pedersen (FP, 2014) consists of selling a portfolio made of high beta stocks' excess returns over the risk free asset and buying a portfolio made of low beta stocks' excess returns (note that the long and short portfolios are both zero-net investments). Additionally, both portfolios are scaled by the inverse of the risky assets' weighted betas, and thus, given that the average Market beta value fluctuates around one, the excess returns of the low beta portfolio are amplified, while the excess returns of the high beta portfolio are reduced. As shown in FP, the BAB factor is a zero-net investment and market-neutral strategy, but it is not dollar-neutral in terms of the risky portfolios.

Modifying the weights used to augment and reduce the long-short portfolios' excess returns modifies the performance of the strategy. To simplify the comparison across different levered strategies, I will use the same weights on all of them. As shown in Frazzini and Pedersen (FP 2014), further calibration of the weights applied to the long-short portfolio strategy can increase the resulting Sharpe Ratios. However, the goal in this paper is not to find the strategy with the largest Sharpe Ratio, but to compare the different possible strategies and identify those that are not priced by the already existing factors. For this purpose I create the following benchmark scenario. Every December I estimate the individual assets' betas and alphas using simple OLS regressions and five-year data. FP suggests calculating the parameters differently than the usual OLS, but again, my goal is not to find the highest Sharpe Ratio nor the largest pricing error but to compare across strategies. Therefore, using the same (most) common technique across strategies to calculate the parameters of interest seems appropriate in this case.

Based on the estimated betas, alphas, and predicted returns, I create a low portfolio and a high portfolio, where the low portfolio contains the assets with estimated parameters below the median value and the high portfolio contains the assets with estimated parameters greater than or equal to the median. Then, the levered strategy consists of buying the low portfolio and selling the high portfolio with certain weights. It is important to stress again that I will use the same weights across all strategies. I will construct the weights as in Horenstein (2017), who follows closely the methodology implemented by FP. The next paragraphs explain how.

For each asset i, $\beta_i = \rho_{iM}\,(\sigma_i/\sigma_M)$, where ρ_{iM} is the correlation between the asset's i returns and the Market returns, while σ_i and σ_M are the asset i and Market estimated volatilities, respectively. As in FP, the ρ_{iM} is estimated using five year data while σ_i and σ_M are estimated using yearly data. The final Market beta assigned to an asset i (β_i^M) is compressed towards one as in FP using the formula $\beta_i^M = 0.6\beta_i + 0.4$.

The low beta portfolios used to calculate the common weights contain all assets with β_i^M lower than the median and the high beta portfolio contains the ones greater than or equal to the median. Securities β_i^M in the corresponding low or high portfolio are weighted using the same formula as in FP. More precisely, let nl be the number of assets in the low beta portfolio and zl be the $nl \times 1$

vector of beta ranks $zl_i = rank(\beta_i^M)$. The weight of an asset i in the low beta portfolio is given by $wl_i = (nl - zl_i + 1)/\sum zl_i$. Similarly, let nh be the number of assets in the high beta portfolio and zh be the $nh \times 1$ vector of beta ranks in this portfolio, where $zh_i = rank(\beta_i^M)$. The weight of an asset i in the high beta portfolio is given by $wh_i = zh_i/\sum zh_i$. Note that $\sum wl_i = \sum wh_i = 1$. The final weighted Market beta of the low and high beta portfolios are $\beta^L = \sum wl_i \beta_i^M$ and $\beta^H = \sum wh_i \beta_i^M$, respectively. The returns of the low and high portfolio are $r^L = \sum wl_i r_i^L$ and $r^H = \sum wh_i r_i^H$, respectively. The BAB strategy's return of selling the high portfolio and buying the low portfolio is $r_{t+s}^{BAB} = \frac{1}{\beta_t^L}(r_{t+s}^L - r_{t+s}^f) - \frac{1}{\beta_t^H}(r_{t+s}^H - r_{t+s}^f)$, where $s = 1, ..., 12$ and t corresponds to December (since the weights β^L and β^H are calculated yearly at the end of December). For every long-short strategy with leverage described in Table 2 I use the same β^L and β^H. On average, the strategies using my estimated weights invest around \$1.67 in the long portfolio and \$0.63 in the short portfolio.

The main difference in the calculation of my weights β^L and β^H and the methodology used in FP is that they use daily data to estimate betas and I use monthly data. Additionally, they allow for assets to have at least three years of data in their calculation, while I use assets with at least five years of data. Finally, they re-balance their strategies (and portfolio weights) monthly while I do it yearly (end of December).

The rationale that supports the modifications in the way I calculate the weights is related to my intention of creating a benchmark scenario to analyze the different levered strategies and can be summarized as follows. First, one of my goals is to compare across strategies using the same method (and weights) for every strategy. Since the highest frequency available for the macroeconomic variables I use is monthly data, I decided to use monthly data for all calculations in every strategy. Second, the other goal of this paper is to check if some of the levered strategies cannot be priced by other factors, like for example the Fama-French five factors. Since the portfolios used to construct the FF factors are re-balanced annually, I decided to use the same frequency to re-balance the strategies in this paper to compare homogeneous scenarios. Strategies with different re-balancing frequencies generate different transaction costs, increasing the likelihood of data-snooping problems (Novy-Marx and Velikov, 2016). Finally, I estimate the alphas and betas of the levered strategies using simple OLS regressions. As it is standard in the literature, I use 60 months of data (5 years) for such estimations. Of course, as previously discussed, there might be different ways to estimate betas and alphas that lead to strategies with better performance metrics. I want to stress again that the goal of this paper is not to find the highest attainable Sharpe Ratio, but to provide insights about which strategies might contain relevant pricing information.

Now I summarize relevant details necessary to construct the different levered strategies used in this paper. For the univariate beta strategies (individual FF5 factors and the ten macroeconomic variables), I obtain the betas by simple OLS regression using five-year data. Macroeconomic variables are used with a 6-month lag to be sure that revised series are available at the moment in which the econometrician runs the regression. Portfolio re-balancing is done each December and the assets in the low and high portfolios are fixed for twelve months. Alphas for the BAA strategies based on buying low alpha stocks and selling high alpha stocks are also based on an alpha's OLS estimations. Finally, BAPR strategies consisting of buying low predicted expected return assets and selling high predicted expected return assets are also based on betas from OLS regressions (times the average value of the factors calculated using the last 60 months).

Figure 1 below shows the monthly Sharpe Ratios generated by all of the strategies analyzed in this paper over the monthly Sharpe Ratio of the Market factor.

[Insert Figure 1 around here]

The Sharpe Ratio of the Market BAB strategy is the largest and more than doubles the Sharpe Ratio of the Market factor. Interestingly, all strategies except the HML BAB and CMA BAB have Sharpe Ratios larger than the Market factor. Strategies based on selling high alpha stock and buying low alpha stocks have large Sharpe Ratios too, almost as large as the one of the Market BAB, especially for the FF5 BAA strategy.[10] Similarly, several strategies based on macroeconomic variables present sizable Sharpe Ratios.

In the next Section I will show that these large Sharpe Ratios might be misleading. More precisely, if a variable is unrelated to risk and its betas generate a flat SML, a levered strategy might still produce large Sharpe Ratios relative to the Market factor simply because of what I call *the mechanical effect of leverage*. Additionally, if we look at a strategy's risk premium, we can always attain positive expected returns in a long-short strategy with leverage independently of whether the factor generating the flat SML is related to risk or not. In fact, a strategy with leverage can attain positive expected returns independently of the SML generated being decreasing, flat, or increasing in a certain factor loading. This can easily be shown as follows. Let $\tilde{r}^L$ and $\tilde{r}^H$ be the returns on a portfolio of risky assets with high and low factor loadings relative to a factor unrelated to risk. For simplicity, let λ and $(1-\lambda)$ be the time-invariant weights on the low and high portfolios of a betting against the factor loading strategy. Without loss of generality, let's assume that $E(\tilde{r}^L) \lesseqqgtr E(\tilde{r}^H) > r^f$. We can always obtain $E(r^{BAB}) = \lambda E(\tilde{r}^L - r^f) - (1-\lambda)E(\tilde{r}^H - r^f) > 0$ by making λ sufficiently close to one. Similarly, if the Sharpe Ratio of $\tilde{r}^L$ is greater than that of the Market factor, a λ sufficiently close to one will suffice to make the strategy appear good in terms of this metric. Note that the weights of this example are not time-varying while those of a BAB strategy are, and as such, they can have a non-linear impact.

In the next Section I will examine whether the mechanical effect of augmenting the impact of the low beta portfolio and reducing that of the high beta one can explain the Sharpe Ratios observed

[10] Horenstein (2017) showed that the BAA factor constructed by rebalancing portfolios every 24 months presents higher Sharpe Ratio and larger pricing errors than when using 12 months for rebalancing. Similarly, the optimal rebalancing period for the Market BAB factor seems to be 1 month. In this paper I just present results using a 12-month rebalancing period across strategies. Again, my objective is to analyze the impact of leverage using the same benchmark scenario for all levered strategies, not to find the strategy with the best performance metrics.

in the strategies analyzed.[11] Importantly, I will also analyze which strategies cannot be priced by standard asset pricing models.

3 Results

3.1 The mechanical effect of leverage

A variable used as a factor but unrelated to risk will most likely lead to a flat SML when sorting portfolios on the estimated factor loadings. Let's call the factor loadings generated by a variable unrelated to risk *random beta*, to distinguish it from the standard (risk-related) beta. A strategy that buys the low random beta portfolio with a weight greater than one and sells the high random beta portfolio with a weight less than one might generate relatively high Sharpe Ratios and/or significant abnormal returns. For example, by chance it could be that ranking assets by random betas assigns a higher proportion of low risk-related beta stocks to the low portfolio than to the high portfolio, making an irrelevant variable appear relevant when used to create a levered strategy.

In this Section I generate the distribution of Sharpe Ratios and alpha's t-statistics of randomly created portfolios to study the mechanical effect of leverage using a simple bootstrap.[12] More precisely, using the same data to create the levered strategies described in Table 2 and Figure 1, every December I randomly assign half of the stocks to a "low" portfolio and the other half to a "high" portfolio. Then, I randomly assigned each assets' i rank zl_i (zh_i) in the low (high) portfolio. Remember that the weight of an asset in a portfolio depends on its rank (see Section 2.2).

As with the strategies described in Table 2, I re-balance the long and short random portfolios once a year, at the end of December. I do this for data from December 1972 to December 2014, which means I generate monthly data on these random portfolios from January 1973 to December 2015. Then, I apply the same weights used in the strategies in the previous Section to the two portfolios and calculate the random levered strategie's Sharpe Ratio, CAPM alpha, Carhart alpha, and FF5 alpha. Additionally, I also compute the Sharpe Ratios and alphas of the low portfolio, high portfolio, and the unlevered low minus high portfolio strategy (unlevered random strategy) for comparison purposes. I repeat this process 100,000 times to get a distribution of the Sharpe Ratios and alpha's t-statistics. The only parameters that remain constant in each iteration of the bootstrap are the weights assigned to the low and high portfolios.

Figure 2 shows the distribution of the parameters of interest for the levered random strategies.

[Insert Figure 2 around here]

[11] According to FP, the weights of the Market BAB strategy capture investors' funding liquidity constraint. Thus, what I call the mechanical effect of leverage might be simply the impact of timing time-varying investors' funding liquidity. However, such impact should affect all of the analyzed BAB strategies similarly. Thus, the name mechanical effect of leverage means simply that it is the effect of the weights on the metrics used to compare the strategies' performances, independently of the variable used to construct the sorted portfolios.

[12] To calculate the t-statistics I use heteroskedastic robust standard-errors.

A conservative interpretation of the figure is that we cannot rule out that the only effect a levered strategy is capturing is the mechanical effect of leverage when the monthly Sharpe Ratios lie in the range (0.13,0.16). For the (unlevered) FF5 Market, SMB, HML, RMW, and CMA factors, the corresponding Sharpe Ratios are 0.11, 0.07, 0.12, 0.11, and 0.17. Therefore, the mechanical effect of leverage (with the weights I use to generate leverage) produces on average higher Sharpe Ratios than any FF5 factor but CMA – up to 50% larger than the Market factor. This result shows the importance of taking into account this effect when analyzing levered strategies in order to avoid false positives.

Additionally, levered random strategies produce on average sizable alpha t-statistics (for the Carhart and FF5 models the average alpha t-statistic is around 3). Therefore, this commonly used measure to determine the adequacy of a strategy leads to false positives too often and does not seem appropriate to assess the performance of levered strategies.

Now, to further study the mechanical effect of leverage, I will compare the distribution of the Sharpe Ratios and alphas' t-statistics of the simulated levered random strategies with those of the unlevered random strategies. The latter is simply the result of subtracting the high portfolio excess returns from the low one without using leverage (while still weighting each asset inside each portfolio by its rank). In terms of the discussion in Section 2.2, the levered strategy is $r^{BAB}_{t+s} = \frac{1}{\beta^L_t}(r^L_{t+s} - r^f_{t+s}) - \frac{1}{\beta^H_t}(r^H_{t+s} - r^f_{t+s})$ while the unlevered one is simply $r^{UnBAB}_{t+s} = r^L_{t+s} - r^H_{t+s}$, where $s = 1, ..., 12$ and t corresponds to December (since the weights β^L and β^H are calculated yearly at the end of December).

The summary statistics are shown in Table 3, the histograms comparing the parameter's distribution from the levered random strategies against the unlevered ones are in Figure 3, and the histograms comparing the parameter's distribution from the levered random strategy against the Low Portfolio are in Figure 4.[13]

[Insert Table 3 around here]

[Insert Figure 3 around here]

[Insert Figure 4 around here]

First let's compare Sharpe Ratios. From Panel (b) of Table 3 and Panel (a) of Figure 3 we observe that the Sharpe Ratios of the unlevered random strategies have a mean of zero. This is

[13] I do not show the histograms comparing the parameter's distribution from the simulated levered random strategies against the simulated random High portfolios since they are almost identical to those of the simulated random Low portfolio.

expexcted since the average values of this parameter for the Low and High portfolio is the same as shown in Panels (c) and (d) of Table 3. The mean and standard deviation of the levered random strategies' Sharpe Ratio are larger than that of the Low and High portfolios separately. The mean Sharpe Ratio is larger by 9% (and the difference is significant at less than 1%), while the maximum value of the Sharpe Ratio for the BAB strategy is larger by 15%. Overall, I find that the weights I use increase the Sharpe Ratio by an average of 9% even if the beta used to construct the portfolio is unrelated to risk; therefore, the mechanical effect of leverage magnifies the Sharpe Ratio of the levered strategies.

Now let's analyze the CAPM, Carhart and FF5 alpha's t-statistics. The unlevered random strategies produced on average alphas' t-statistics equal to zero [Table 3 Panel (b)]. Panels (c) and (d) of Table 3 show that the CAPM and FF5 alpha's t-statistics are on average significantly less than 2 for the Low and High portfolio, while the Carhart's alpha t-statistic is higher than 3. It seems that adding the Momentum factor as a regressor increases the chances of finding statistically significant pricing errors. However, the CAPM and FF5 models seem to properly price the randomly created portfolios, especially if we take into account the threshold suggested by Harvey et al. (2016) of using t-statistics greater than 3. Surprisingly, for the case of levered strategies the CAPM seems to generate statistically significant alphas less often than FF5 [Panel (a)]. The alphas' t-statistics generated by FF5 increase dramatically once I use leverage, as depicted by an average t-statistic of 3.12.

To sum up the results from our simulations, I found that the impact of the mechanical effect of leverage on both parameters, Sharpe Ratios and alpha's t-statistics, is non-negligible. Once I apply leverage to a long-short strategy, the possibilities of confounding an irrelevant factor as a relevant one are quite high.

In the next Section, I analyze more in depth the performance metrics of the strategies described in Table 2, as well as the possibility that some of them appear relevant simply because of the mechanical effect of leverage.

3.2 Portfolio characteristics and performance of strategies with leverage

In this Section I analyze the characteristics of each levered strategy presented in Table 2. I start by showing in Table 4 the summary statistics for the twenty levered strategies between January 1973 and December 2015.[14] For each strategy the table reports summary statistics for the low portfolio, high portfolio, and levered strategy (weighted low beta/alpha/predicted return portfolio minus weighted high beta/alpha/predicted return portfolio). It reports the monthly average excess return, monthly CAPM alpha, monthly Carhart alpha, monthly FF5 alpha, monthly Sharpe Ratio, and average size of the weighted portfolios (in thousands of USD) at the time of re-balancing.[15]

[14]Our stock return data starts in January 1968 (macroeconomic data starts on July 1967), but our levered strategies data start in January 1973 since I use five years of data to initialize the calculations.

[15]I do not annualize the estimated monthly Sharpe Ratios to avoid aggregation issues [see Lo (2002)].

[Insert Table 4 around here]

Before analyzing the strategies in detail, and consistent with my simulation results, almost all of them produce CAPM, Carhart, and FF5 pricing errors that are statistically significant at the 1% level or less. Additionally, I already showed in Figure 1 that all strategies except two produce Sharpe Ratios that are higher than that of the Market factor. In the previous Section we find that to rule out the mechanical effect of leverage, we should ask strategies to have a monthly Sharpe Ratio greater than 0.16. This allow us to remove from the set of relevant strategies the RMW BAB strategy and many of the strategies based on macroeconomic variables (ΔLabor Participation, ΔPersonal Savings Rate, ΔReal Personal Consumption, and ΔNew One Family Houses Sold). However, this metric still keeps as possibly relevant strategies 15 out of the 20 strategies. Therefore, if a researcher chose relevant strategies based solely on these two metrics – alphas and Sharpe Ratios – without further analysis, then too many strategies seem worth pursuing.

Panels A through E report the results for the levered strategies using the betas from each of the FF5 factors individually. The highest Sharpe Ratio is that of the Market BAB strategy, followed by the SMB BAB strategy, which more than doubles the Sharpe Ratio of the other strategies in this group. The main difference between the Market BAB and SMB BAB strategies and the others is that they show a decreasing Sharpe Ratio on the portfolios sorted on factors' betas. Therefore, a decreasing Sharpe Ratio on betas seems important for the performance of a BAB strategy. Similarly, someone could be interested in using a strategy in favor of beta for the cases in which the Sharpe Ratio is increasing on the factor loadings, like the case of sorting portfolios based on HML or CMA betas. Using the same fixed weights I used in every strategy, but buying the high HML beta portfolio and shorting the low beta one (the reverse of a BAB strategy), I obtain a strategy with a monthly Sharpe Ratio of 0.21. However, the FF5 alpha of such strategy is not statistically significant. Similar results are obtained with the low and high portfolios based on the CMA factor's betas.[16]

The second type of levered strategy I analyze is the BAA based on selling a portfolio of high alpha stocks and buying a portfolio of low alpha stocks. The results from these strategies are in panels F to H. The Sharpe Ratios of these strategies are second in magnitude only to the Market BAB strategy, and all of them show a decreasing pattern in the portfolio's Sharpe Ratio. All the strategies present abnormal returns that are statistically significant at the 1% level or less (with unreported t-stat values greater than 4). Additionally, as shown in Horenstein (2017), all these strategies are highly correlated among themselves (with a correlation coefficient around 0.95)

The third set of strategies I analyze are those based on selling a portfolio of assets with high predicted expected returns and buying assets with low predicted expected returns (panels I and J). Coherent with Barber et al.'s (2016) finding that investors treat exposures to factors other than

[16]Details about these results are available from the author upon request.

the Market as alpha, these strategies are quite correlated with the BAA strategies I discussed in the previous paragraph (with correlation coefficients between 0.78 and 0.87). However, small stocks have a lesser weight on the low portfolio of the BAPR strategies. These strategies present decreasing Sharpe Ratios in the sorted portfolios and statistically significant alphas for the three factor models I control for at less than the 1% level of significance.

The fourth and last set of levered strategies I analyze is of strategies formed on sensitivities to macroeconomic variables. Results are presented in panels K to T. Some of the strategies present deceasing Sharpe Ratios on the sorted portfolios while others do not. However, all of them present statistically significant alphas when regressing the strategies against the CAPM, Carhart, and FF5 factor models. These results warn us again about some levered strategies appearing successful simply because of the leverage (and de-leverage) applied to portfolios with similar expected returns and/or Sharpe Ratios, independently of whether the betas used to sort the assets are related to a source of common risk or not. Nevertheless, there are still some macroeconomic variables that generate sizable monthly Sharpe Ratios for the BAB strategies, while showing decreasing Sharpe Ratios in the sorted portfolios, like for example the Default Spread BAB strategy shown in Panel T or the ΔUnemployment BAB strategy showed in Panel L.

Summarizing the results in this section, first we can conclude that the levered strategies that present the highest Sharpe Ratios are those whose sorted portfolios on betas/alphas/predicted returns show a decreasing pattern in Sharpe Ratios. Second, a decreasing pattern in Sharpe Ratios is more important than a decreasing pattern in expected returns to generate levered strategies with high Sharpe Ratios. The strategy with the highest Sharpe Ratio is the Market BAB, but the portfolios sorted by Market beta show an increasing pattern in average excess returns, while many other portfolios show a flat or even decreasing pattern of excess returns (e.g. HML BAB in Panel C or ΔPersonal Savings Rate in Panel N).

Although the mechanical effect of leverage can lead to high Sharpe Ratios and statistically significant abnormal returns independently of whether the factor loadings are related to a risk or not, many of the strategies I analyzed in this Section present Sharpe Ratios that are too high to be considered the sole product of this mechanical effect of leverage. These strategies are the Market BAB, SMB BAB, CAPM BAA, Carhart BAA, FF5 BAA, Carhart BAPR, FF5 BAPR, Inflation BAB, ΔUnemplyment BAB, ΔAvg Hour Earn BAB, ΔNew Housing Auth BAB, ΔNew Houses Prc BAB, and Default Spread BAB. Now the obvious question is how many of these strategies are redundant. I study this question in the next Section.

3.3 The minimum set of levered strategies that price all others

The results of the previous Section show that the high Sharpe Ratios of some of the levered strategies I analyzed are unlikely to be due to the mechanical effect of leverage (especially those whose Sharpe Ratios are around 0.20). An important question that remains to be answered, especially for those interested in constructing better asset pricing models, is how many of these levered strategies are not priced by the others. To answer this question I use the insight from Barillas and Shanken (2017). They showed that for the case of tradable factors "it turns out that test assets tell us nothing about model comparison, beyond what we learn by examining the extent to which each model prices the factors in the other models." In other words, to compare factor models we can simply regress one factor against another set of factors and see if the pricing error is statistically significant. If it is, then the factor used as an independent variable can be added to the model to improve it. Importantly, the results on Section 3.1 show that regressing levered strategies on models with unlevered factors produce statistically significant alphas too often. This Section's results will show that levered strategies' alphas become insignificant once we control for a model containing levered factors.

I first run univariate regressions of all strategies against each other to study which ones can price other strategies and which ones cannot. Table 5 below shows the significance levels of 380 regressions obtained from regressing each of the twenty levered strategies on the other nineteen. Rows are assigned to the strategies used as dependent variables while columns are assigned to the strategies used as regressors. For example, the first row corresponds to the significance level of the alpha's t-statistics obtained using the Market BAB strategy as dependent variable and all other strategies as independent. We see from the first row that the Market BAB strategy is not priced by any other strategy, since the pricing errors of the univariate regressions are statistically significant at the 1% level or less, as shown by the three stars in every cell.

[Insert Table 5 around here]

Besides the Market BAB, the only other strategy that is not priced by any other one is the FF5 BAA. Additionally, the first column shows that the Market BAB strategy fails to price all BAA, BAPR, and some macroeconomic BAB strategies. At the same time, the column corresponding to FF5 BAA shows that those strategies that the Market BAB fails to price (cells with three stars in the first column), are priced by the FF5 BAA strategy (those that have less than 3 stars in the FF5 BAA column). Therefore, it seems that the two strategies contained all the relevant information for pricing purposes in the set of twenty strategies. To corroborate this, I present in Table 6 below the results from using a two-factor model with the Market BAB and FF5 BAA strategies as factors and all other levered strategies as independent variables.

[Insert Table 6 around here]

Table 6 shows that the Market BAB and FF5 BAA strategies are able to price all other levered factors used in this paper. In unreported results available upon request, I obtained similar results when replacing the FF5 BAA for either the CAPM BAA, Carhart BAA, Carhart BAPR, and FF5 BAPR. Consistent with the results in Horenstein (2017), a strategy of betting against alpha seems promising as it is not priced by the Market BAB or any other factor, while it prices the levered strategies that the Market BAB fails to price.

To sum up, it transpires from these results that if a researcher wants to use alpha as a metric for assessing the relevance of a factor constructed using leverage, controlling for common risk using a model with levered factors is a must. The usual models with unlevered factors like for example FF5 do not seem reliable when testing levered strategies.

4 Concluding remarks

This paper is concerned with the impact of using Sharpe Ratios and alphas when assessing long-short strategies constructed using leverage like Frazzini and Pedersen's (2014) Betting Against Beta (BAB) and Horenstein's (2017) Betting Against Alpha (BAA).

Simulating 100,000 strategies that randomly assign assets to the low and high portfolio of a levered strategy, and using similar weights to apply leverage as in Frazzini and Pedersen's BAB strategy, I find that monthly Sharpe Ratios are on average 20% larger than that of the empirical market factor and up to 50% larger. These simulated strategies also tend to produce CAPM, Carhart, and FF5 alpha t-statistics that are highly significant, easily surpassing the hurdle of 3.0 suggested by Harvey et al. (2016). I call this the mechanical effect of leverage on performance metrics.

For testing purposes I also create 20 different levered strategies using the same weights to apply leverage as those of the BAB strategy. To assign assets to the low and high portfolios, 15 of these 20 strategies sort the stocks by betas generated by the FF5 factors individually and ten macroeconomic variables. I also create 3 BAA strategies by sorting assets by the estimated alphas from the CAPM, FF5, and Carhart model. Finally, I create 2 strategies assigning assets to the low and high portfolio based on the predicted returns from the Carhart and FF5 models. I find that many of these strategies seem useful and produce sizable Sharpe Ratios that cannot be explained by the mechanical effect of leverage. However, and consistent with the results in Horenstein (2017), I find that two strategies suffice to price all others: the Market BAB strategy used in tandem with any of the BAA ones.

Based on all these findings I propose three diagnostic tests for checking the relevance of a tradable long-short strategy constructed using leverage. First, a strategy's monthly Sharpe Ratios should be large enough to rule out being a product of the mechanical effect of leverage (at least 50% larger than the Market factor's Sharpe Ratio). Second, Sharpe Ratios should decrease across portfolios sorted on the metric used to construct the levered strategy. Third, a new levered strategy should produce statistically significant alphas when the risk is controlled by a model containing the Market BAB and the FF5 BAA as factors.[17] Controlling common risk using models with only unlevered

[17]The FF5 BAA factor can be replaced by the CAPM BAA factor or the Carhart BAA factor.

factors like the standard CAPM, Carhart, or FF5 models to estimate the pricing errors of a levered strategy produces false positives too often.

Of course there are other methods for testing whether a new proposed factor captures relevant information missed by the already existing ones. For example, Ahn et al. (2017) and Burnside (2016) suggest using rank estimation methods. Feng et al. (2017) proposed a model selection method based on applying a double-selection LASSO in tandem with a two-pass regression. Horenstein (2017) uses rank estimation methods to confirm the relevance of the BAA factor. In this paper I focus on Sharpe Ratios and estimated alphas, arguably the two most common performance metrics used in the literature when analyzing tradable factors.

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Table 1: Macroeconomic variables

This table describes the ten macroeconomic variables used in our study. The first column reports the name of the variable. The second column explain how the variable was constructed, and the third column reports the name of the variable in the FRED database. All variables have been downloaded from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org).

Variable	Construction	FRED Series
Inflation	Monthly change in the Consumer Price Index	CPIAUCSL
Δ Unemployment	Monthly change in Civilian Unemployment Rate	UNRATE
Δ Labor Part	Monthly change in Civilian Labor Force Participation Rate	CIVPART
Δ Pers Savings	Monthly change in Personal Saving Rate	PSAVERT
Δ Real Pers Cons	Monthly change in Real Personal Consumption Expenditures	DPCERAM1M225NBEA
Δ Avg Hour Earn	Monthly change in Average Hourly Earnings of Production and Nonsupervisory Employee	AHETPI
Δ New Housing Auth	Monthly change in New Private Housing Units Authorized by Building Permits	PERMIT
Δ New Houses Prc	Monthly change in Median Sales Price for New Houses Sold	MSPNHSUS
Δ New Houses Sold	Monthly change in New One Family Houses Sold	HSN1F
Default Premium	Difference between BAA-rated and AAA-rated corporate bonds	BAA10YM, AAA10YM

Table 2: Levered strategies' description

This table describes the twenty levered long-short strategies used in this study. Each strategy consists of selling a portfolio containing high beta (or alpha or predicted returns) stocks' excess return over the risk free asset and buying a portfolio of low beta (or alpha or predicted returns) stocks' excess returns. There are fifteen strategies based on sorting assets by betas obtained from univariate OLS regressions. Five of them use the betas from each of the Fama-French five factors (Market BAB, SMB BAB, HML BAB, RMW BAB, and CMA BAB) and ten use the betas from the macroeconomic variables described in Table 1. The macroeconomic variables are used with a 6-month lag to guarantee that revised series are available at the moment in which the econometrician runs the regression. Additionally, three strategies are constructed by sorting assets on their CAPM, Carhart, and FF5 alphas (CAPM BAA, Carhart BAA, and FF5 BAA). Two strategies are obtained by sorting assets on the predicted returns by the Carhart and FF5 models (Carhart BAPR and FF5 BAPR). Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage. The macroeconomic variables are from the Federal Reserve Bank of St. Louis webpage.

Strategy	Short description
Market BAB	Strategy short on assets with higher than the median MKT beta and long in assets with lower than the median MKT beta
SMB BAB	Strategy short on assets with higher than the median SMB beta and long in assets with lower than the median SMB beta
HML BAB	Strategy short on assets with higher than the median HML beta and long in assets with lower than the median HML beta
RMW BAB	Strategy short on assets with higher than the median RMW beta and long in assets with lower than the median RMW beta
CMA BAB	Strategy short on assets with higher than the median CMA beta and long in assets with lower than the median CMA beta
CAPM BAA	Strategy short on assets with higher than the median CAPM alpha and long in assets with lower than the medianCAPM alpha
Carhart BAA	Strategy short on assets with higher than the median Carhart alpha and long in assets with lower than the median Carhart alpha
FF5 BAA	Strategy short on assets with higher than the median FF5 alpha and long in assets with lower than the median FF5 alpha
Carhart BAPR	Strategy short on assets with higher than the median predicted expected returns by the Carhart model and long in the others
FF5 BAPR	Strategy short on assets with higher than the median predicted expected returns by the FF5 model and long in the others
Inflation BAB	Strategy short on assets with higher than the median Inflation's loading and long in the others
Δ Unemployment BAB	Strategy short on assets with higher than the median Δ Unemplyment's loading and long in the others
Δ Labor Part BAB	Strategy short on assets with higher than the median Δ Labor Part's loading and long in the others
Δ Pers Savings BAB	Strategy short on assets with higher than the median Δ Pers Savings's loading and long in the others
Δ Real Pers Cons BAB	Strategy short on assets with higher than the median Δ Real Pers Cons's loading and long in the others
Δ Avg Hour Earn BAB	Strategy short on assets with higher than the median Δ Avg Hour Earn's loading and long in the others
Δ New Housing Auth BAB	Strategy short on assets with higher than the median Δ New Housing Auth's loading and long in the others
Δ New Houses Prc BAB	Strategy short on assets with higher than the median Δ New Houses Prc's loading and long in the others
Δ New Houses Sold BAB	Strategy short on assets with higher than the median Δ New Houses Sold's loading and long in the others
Default Premium BAB	Strategy short on assets with higher than the median Default Premium's loading and long in the others

Table 3: Simulations' summary statistics

This table presents the statistics of different performance metrics' distributions calculated using 100,000 simulated levered strategies. The statistics are the mean, standard deviation, maximum, and minimum values of the generated empirical distribution. The performance metrics are the Sharpe Ratios and the heteroskedastic robust t-statistics generated by regressing each simulated strategy on the following three models: CAPM, Carhart, and FF5. The simulated strategies are generated by randomly assigning half of the stocks to a "low" portfolio and the other half to a "high" portfolio at the end of every December. Then, I randomly assigned each assets' i rank zl_i (zh_i) in the low (high) portfolio. The weight of an asset in a portfolio depends on its rank (see Section 2.2). I do this for data from December 1972 to December 2014, which means I generate monthly data on these random portfolios from January 1973 to December 2015. Panel (a) shows the distribution results from the 100,000 levered strategy (low-high portfolio with leverage), where I apply the same leverage to each strategy (see Section 2.2). Panel (b) shows the statistics for the performance metrics of a strategy consisting of subtracting the high portfolio from the low one without applying leverage. Panels (c) and (d) show the statistics for the performance metrics of the Low and High portfolio respectively. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage.

	Mean	Std. Dev.	Min	Max	95% Interval
(a) Levered Strategies					
Sharpe Ratio	0.147	0.004	0.131	0.163	[0.140 , 0.154]
CAPM's alpha t-statistic	2.195	0.143	1.554	2.840	[1.917 , 2.475]
Carhart's alpha t-statistic	2.940	0.172	2.140	3.734	[2.606 , 3.278]
FF5's alpha t-statistic	3.118	0.195	2.288	3.997	[2.739 , 3.503]
(b) Unlevered Strategies					
Sharpe Ratio	0.000	0.044	-0.204	0.214	[-0.086 , 0.086]
CAPM's alpha t-statistic	-0.001	0.985	-4.643	4.787	[-1.918 , 1.925]
Carhart's alpha t-statistic	-0.002	1.004	-4.425	4.725	[-1.974 , 1.978]
FF5's alpha t-statistic	-0.003	1.031	-4.610	4.899	[-2.021 , 2.023]
(c) Low Portfolio					
Sharpe Ratio	0.135	0.002	0.128	0.142	[0.132 , 0.132]
CAPM's alpha t-statistic	1.714	0.069	1.410	2.032	[1.579 , 1.851]
Carhart's alpha t-statistic	3.117	0.142	2.529	3.767	[2.838 , 3.395]
FF5's alpha t-statistic	1.297	0.132	0.728	1.905	[1.038 , 1.556]
(d) High Portfolio					
Sharpe Ratio	0.135	0.002	0.128	0.142	[0.132 , 0.138]
CAPM's alpha t-statistic	1.715	0.070	1.392	2.020	[1.578 , 1.850]
Carhart's alpha t-statistic	3.117	0.142	2.464	3.691	[2.839 , 3.396]
FF5's alpha t-statistic	1.298	0.132	0.687	1.872	[1.037 , 1.556]

Table 4: Levered strategies' summary statistics

This table presents the monthly performance metrics for the low beta/alpha/predicted return portfolios, high beta/alpha/predicted return portfolios, and low minus high strategy using realized betas from univariate regressions on the Market (Panel A), SMB (Panel B), HML (Panel C), RMW (Panel D), CMA (Panel E). I use realized alphas to sort portfolios based on the CAPM's alpha (Panel F), Carhart's alpha (Panel G), and FF5's alpha (Panel H). I used realized predicted returns (estimated betas times the factors' risk premiums) to sort portfolios from Carhart (Panel I) and FF5 (Panel J). Panels K to T use betas from univariate regression on macroeconomics variables to construct the low and high portfolios. The ten macroeconomic variables are described in Table 1. The macroeconomic variables are used with a 6-month lag to guarantee that revised series are available at the moment in which the econometrician runs the regression. The performance metrics are the monthly Sharpe Ratios, monthly Excess Returns over the one-month T-bill, and abnormal returns for the CAPM, Carhart (1997), and Fama-French Five Factor (FF5, 2015) models. The abnormal returns are estimated by OLS and their significance levels are calculated using heteroskedastic robust standard errors. The variable Size corresponds to the weighted market cap value of the portfolios. The Low, High, and Low-High portfolios are weighted with the same weights across strategies. The column Low (High) shows the results for the portfolio containing assets with realized betas/alphas/predicted returns below (above) the median value at the moment of rebalancing. Betas and alphas used to assign the assets to the low and high portfolios are estimated with OLS. I use 5-year data to calculate betas and alphas. Portfolios are rebalanced yearly, at the end of December. I use monthly data from January 1968 – December 2015 to construct portfolios for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage. The macroeconomic variables are from the Federal Reserve Bank of St. Louis webpage.

	Low Beta	High Beta	Low - High
	A) Market BAB		
Excess Return	0.81%	0.90%	0.79%
CAPM alpha	0.47%***	0.18%	0.73%***
Carhart alpha	0.30%***	0.27%***	0.40%***
FF5 alpha	0.22%***	0.10%	0.40%***
Sharpe Ratio	0.22	0.12	0.26
Size	$1,648,315	$1,566,048	
	B) SMB BAB		
Excess Return	0.75%	1.01%	0.62%
CAPM alpha	0.37%***	0.32%**	0.48%***
Carhart alpha	0.28%***	0.32%***	0.34%***
FF5 alpha	0.15%***	0.22%**	0.21%*
Sharpe Ratio	0.20	0.13	0.20
Size	$3,691,528	$633,444	
	C) HML BAB		
Excess Return	0.75%	1.00%	0.79%
CAPM alpha	0.12%	0.53%***	0.05%
Carhart alpha	0.33%***	0.23%***	0.69%***
FF5 alpha	0.25%***	0.07%	0.84%***
Sharpe Ratio	0.11	0.19	0.08
Size	$1,951,898	$1,574,704	
	D) RMW BAB		
Excess Return	1.01%	0.71%	1.33%
CAPM alpha	0.38%**	0.25%**	0.58%*
Carhart alpha	0.42%***	0.13%*	0.87%***
FF5 alpha	0.37%***	-0.08%	1.07%***
Sharpe Ratio	0.15	0.15	0.13
Size	$1,065,041	$2,664,552	
	E) CMA BAB		
Excess Return	0.85%	0.89%	1.02%
CAPM alpha	0.19%	0.45%***	0.21%
Carhart alpha	0.35%***	0.18%**	0.77%***
FF5 alpha	0.22%**	0.07%	0.81%***
Sharpe Ratio	0.12	0.19	0.10
Size	$1,882,176	$1,540,626	

	Low Pflio	High Pflio	Low - High
	F) CAPM BAA		
Excess Return	1.15%	0.67%	1.60%
CAPM alpha	0.60%***	0.10%	1.10%***
Carhart alpha	0.55%***	0.06%	1.12%***
FF5 alpha	0.33%***	0.00%	0.90%***
Sharpe Ratio	0.18	0.12	0.22
Size	$1,358,710	$1,990,035	
	G) Carhart BAA		
Excess Return	1.13%	0.70%	1.52%
CAPM alpha	0.60%***	0.11%	1.05%***
Carhart alpha	0.46%***	0.15%***	0.86%***
FF5 alpha	0.24%**	0.10%*	0.62%***
Sharpe Ratio	0.18	0.12	0.23
Size	$1,065,909	$2,038,321	
	H) FF5 BAA		
Excess Return	1.15%	0.68%	1.56%
CAPM alpha	0.62%***	0.08%	1.10%***
Carhart alpha	0.47%***	0.13%**	0.89%***
FF5 alpha	0.24%**	0.09%*	0.63%***
Sharpe Ratio	0.19	0.11	0.24
Size	$1,314,520	$1,864,855	
	I) Carhart BAPR		
Excess Return	1.04%	0.79%	1.36%
CAPM alpha	0.52%	0.21%	0.91%***
Carhart alpha	0.54%	0.09%	1.09%***
FF5 alpha	0.33%	0.02%	0.89%***
Sharpe Ratio	0.18	0.13	0.21
Size	$2,097,532	$1,580,973	
	J) FF5 BAPR		
Excess Return	1.00%	0.84%	1.25%
CAPM alpha	0.47%***	0.27%**	0.76%***
Carhart alpha	0.48%***	0.13%**	0.96%***
FF5 alpha	0.30%***	0.04%	0.82%***
Sharpe Ratio	0.17	0.15	0.19
Size	$1,563,465	$1,769,437	

	Low Beta	High Beta	Low - High
	K) Inflation BAB		
Excess Return	0.92%	0.87%	1.06%
CAPM alpha	0.38%***	0.30%**	0.56%***
Carhart alpha	0.34%***	0.23%***	0.60%***
FF5 alpha	0.19%***	0.12%***	0.52%***
Sharpe Ratio	0.16	0.14	0.17
Size	$1,471,133	$1,810,149	
	L) Δ Unemployment BAB		
Excess Return	0.99%	0.84%	1.20%
CAPM alpha	0.45%***	0.28%**	0.69%***
Carhart alpha	0.42%***	0.18%**	0.76%***
FF5 alpha	0.27%***	0.07%	0.69%***
Sharpe Ratio	0.17	0.14	0.20
Size	$2,006,288	$1,188,775	
	M) Δ Labor Participation BAB		
Excess Return	0.93%	0.88%	1.06%
CAPM alpha	0.36%***	0.34%***	0.48%***
Carhart alpha	0.25%***	0.31%***	0.41%***
FF5 alpha	0.19%***	0.12%*	0.55%***
Sharpe Ratio	0.16	0.16	0.16
Size	$1,642,572	$1,584,692	
	N) Δ Personal Savings Rate BAB		
Excess Return	0.99%	0.80%	1.21%
CAPM alpha	0.40%***	0.30%***	0.58%***
Carhart alpha	0.38%***	0.20%***	0.73%***
FF5 alpha	0.30%***	0.03%	0.80%***
Sharpe Ratio	0.16	0.15	0.16
Size	$1,379,864	$1,759,873	
	O) Δ Real Personal Consumption BAB		
Excess Return	0.86%	0.95%	0.91%
CAPM alpha	0.30%**	0.41%***	0.35%**
Carhart alpha	0.21%***	0.35%***	0.32%**
FF5 alpha	0.12%*	0.20%***	0.39%***
Sharpe Ratio	0.15	0.17	0.14
Size	$1,470,632	$1,635,500	

	Low Beta	High Beta	Low - High
	P) Δ Average Hourly Earnings BAB		
Excess Return	0.97%	0.86%	1.13%
CAPM alpha	0.43%***	0.29%**	0.65%***
Carhart alpha	0.30%***	0.30%***	0.46%***
FF5 alpha	0.14%**	0.21%***	0.37%***
Sharpe Ratio	0.17	0.14	0.20
Size	$1,460,885	$1,620,558	
	Q) Δ New Private Housing BAB		
Excess Return	0.95%	0.85%	1.12%
CAPM alpha	0.39%***	0.30%**	0.56%***
Carhart alpha	0.33%***	0.24%***	0.60%***
FF5 alpha	0.23%***	0.08%	0.63%***
Sharpe Ratio	0.16	0.15	0.17
Size	$1,271,184	$2,082,105	
	R) Δ Median Sales Prc for New Houses BAB		
Excess Return	1.00%	0.82%	1.20%
CAPM alpha	0.45%***	0.27%**	0.68%***
Carhart alpha	0.33%***	0.27%***	0.56%***
FF5 alpha	0.20%**	0.14%**	0.53%***
Sharpe Ratio	0.17	0.14	0.20
Size	$1,522,384	$1,543,852	
	S) Δ New One Family Houses Sold BAB		
Excess Return	0.93%	0.88%	1.06%
CAPM alpha	0.37%***	0.33%***	0.51%***
Carhart alpha	0.29%***	0.28%***	0.52%***
FF5 alpha	0.20%***	0.10%	0.59%***
Sharpe Ratio	0.16	0.15	0.16
Size	$1,349,336	$1,853,359	
	T) Default Spread BAB		
Excess Return	1.02%	0.80%	1.31%
CAPM alpha	0.48%***	0.22%*	0.82%***
Carhart alpha	0.50%***	0.10%	0.99%***
FF5 alpha	0.28%***	0.06%	0.76%***
Sharpe Ratio	0.18	0.13	0.21
Size	$1,896,672	$1,223,148	

Table 5: Significant t-statistics from all possible univariate regressions of the levered strategies

This table shows the pricing errors' significance levels obtained from regressing each of the twenty levered strategies on the other nineteen individually. Significance levels are calculated using heteroskedastic robust standard errors. Rows are assigned to the strategies used as dependent variables, while columns are assigned to the strategies used as regressors. For example, the first row corresponds to the significance level of the alpha's t-statistics obtained using the Market BAB strategy as the dependent variable and all other strategies as independent. The twenty strategies are described in Table 2. The Low, High, and Low-High portfolios used to construct the strategies are weighted with the same weights across strategies. Betas and alphas used to assign the assets to the low and high portfolios are estimated with OLS. I use 5-year data to calculate betas and alphas. Portfolios are rebalanced yearly, at the end of December. I use monthly data from January 1968 – December 2015 to construct portfolios for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage. The macroeconomic variables are used with a 6-month lag to guarantee that revised series are available at the moment in which the econometrician runs the regression. The macroeconomic variables are from the Federal Reserve Bank of St. Louis webpage.

	Independent Variable																			
Dependent Variable	Market BAB	SMB BAB	HML BAB	RMW BAB	CMA BAB	CAPM BAA	Carhart BAA	FF5 BAA	Carhart BAPR	FF5 BAPR	Inflation BAB	Δ Unemp BAB	Δ Labor Part BAB	Δ Pers Savings BAB	Δ Real Pers Cons BAB	Δ Avg Hour Earn BAB	Δ New Housing Auth BAB	Δ New Houses Prc BAB	Δ New Houses Sold BAB	Default Premium BAB
Market BAB	--	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
SMB BAB		--	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***
HML BAB	*		--	*	*	**	*	*	***	***	*	***	**	***		*	***	***	***	**
RMW BAB	**	**	***	--	**				**	*		**					*			
CMA BAB		*	**		--	**	*	*	***	***		***	**	***		*	**	***	**	**
CAPM BAA	***	***	***	***	***	--				**	***	**	***	***	***	**	***	**	***	**
Carhart BAA	***	***	***	***	***	*	--	*	**	***	***	***	***	***	***	**	***	**	***	**
FF5 BAA	***	***	***	***	***	***	***	--	***	***	***	***	***	***	***	***	***	***	***	***
Carhart BAPR	***	***	***	***	***				--	***	***	**	***	***	***	**	***	**	***	*
FF5 BAPR	***	***	***	***	***					--	**		**	**	***	*	**		**	
Inflation BAB	**	**	***	***	***						--				**					
Δ Unemployment BAB	***	***	***	***	***					*	**	--	***	***	***		**		***	
Δ Labor Part BAB	**	**	***	**	***								--		**					
Δ Pers Savings BAB	**	**	***	**	***									--	*					
Δ Real Pers Cons BAB		**	***	***	**			*							--			**		
Δ Avg Hour Earn BAB	**	***	***	***	***					*	**		***	***	***	--	**		***	
Δ New Housing Auth BAB	**	**	***	***	***										***		--			
Δ New Houses Prc BAB	**	***	***	***	***						**		***	***	***		**	--	***	
Δ New Houses Sold BAB	**	**	***	**	***										**				--	
Default Premium BAB	***	***	***	***	***	**			*	**	***	*	***	***	***	**	***	**	***	--

* 10%, ** 5%, *** 1%

Table 6: Results from a two-factor model using the Market BAB and FF5 BAA as factors

The table reports regression results using a two factor model containing two levered strategies as regressors: The Marktet BAB and the FF5 BAA. The parameters reported are the estimated alpha and the estimated betas. Significance levels are calculated using heteroskedastic robust standard errors. As dependent variable I use the other eighteen levered strategies analyzed in this paper (see Table 2). The Low, High and Low-High portfolios used to construct the strategies are weighted with the same weights across strategies. Betas and alphas used to assign the assets to the low and high portfolios are estimated with OLS. I use 5-year data to calculate betas and alphas. Portfolios are rebalanced yearly, at the end of December. I use monthly data from January 1968 – December 2015 to construct portfolios for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage. The macroeconomic variables are used with a 6-month lag to guarantee that revised series are available at the moment in which the econometrician runs the regression. The macroeconomic variables are from the Federal Reserve Bank of St. Louis webpage.

	α	β_{MKT_BAB}	β_{FF5_BAA}	R^2
SMB BAB	0.001	0.68***	0.02	0.42
HML BAB	-0.001	-0.92***	1.02***	0.42
RMW BAB	0.000	0.89***	1.27***	0.59
CMA BAB	0.000	-1.13***	1.20***	0.56
CAPM BAA	0.001	-0.31***	1.13***	0.91
Carhart BAA	-0.001	-0.04	1.03***	0.98
Carhart BAPR	0.003*	-0.30***	0.82***	0.63
FF5 BAPR	0.002	-0.35***	0.84***	0.64
Inflation BAB	0.000	-0.22**	0.82***	0.68
Δ Unemployment BAB	0.001	-0.24***	0.80***	0.69
Δ Labor Part BAB	-0.001	-0.24**	0.86***	0.68
Δ Pers Savings BAB	0.001	-0.58***	0.97***	0.61
Δ Real Pers Cons BAB	-0.003	-0.12	0.81***	0.64
Δ Avg Hour Earn BAB	-0.001	0.05	0.76***	0.79
Δ New Housing Auth BAB	0.000	-0.26***	0.82***	0.61
Δ New Houses Prc BAB	0.000	-0.04	0.80***	0.74
Δ New Houses Sold BAB	0.000	-0.16	0.78***	0.57
Default Premium BAB	0.003*	-0.25**	0.75***	0.56

* 10%, ** 5%, *** 1%

Figure 1: Levered strategies' monthly Sharpe Ratios relative to the Market factor

This figure shows the monthly Sharpe Ratio of each of the twenty levered strategies analyzed in this paper relative to the monthly Sharpe Ratio of the CAPM's Market factor. The twenty strategies are described in Table 2. The Low, High, and Low-High portfolios used to construct the strategies are weighted with the same weights across strategies. Betas and alphas used to assign the assets to the low and high portfolios are estimated with OLS. I use 5-year data to calculate betas and alphas. Portfolios are rebalanced yearly, at the end of December. I use monthly data from January 1968 – December 2015 to construct portfolios for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage. The macroeconomic variables are used with a 6-month lag to guarantee that revised series are available at the moment in which the econometrician runs the regression. The macroeconomic variables are from the Federal Reserve Bank of St. Louis webpage.

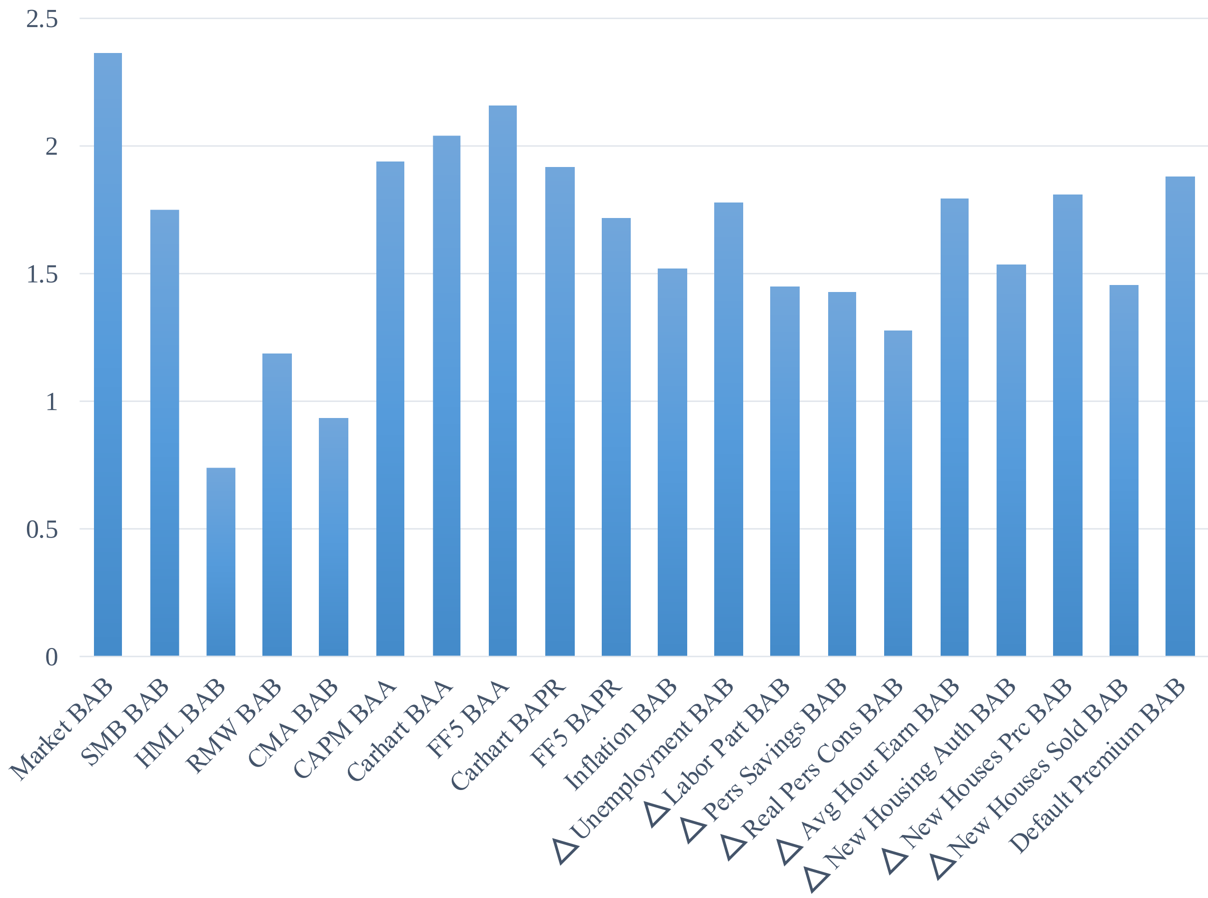
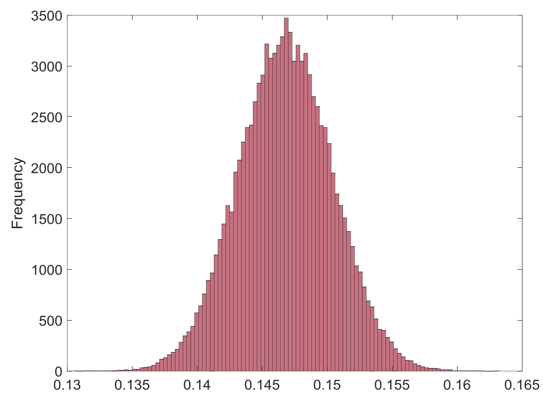


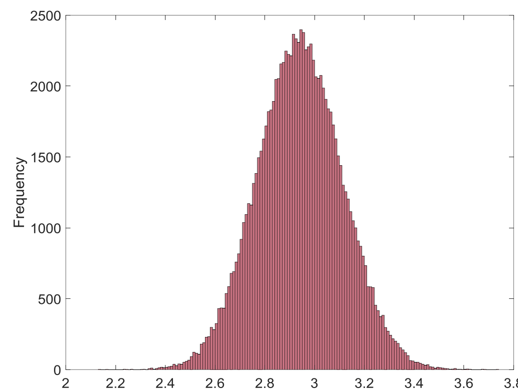
Figure 2: Distribution of 100,000 simulated Sharpe ratios and abnormal returns' t-statistics of simulated BAB strategies

This figure presents the empirical distribution of different performance metrics' calculated using 100,000 simulated levered strategies. The performance metrics are the Sharpe Ratio [Panel (a)] and the heteroskedastic robust t-statistics generated by regressing each simulated strategy on the following three models: CAPM, Carhart, and FF5 [Panels (c) to (d)]. The simulated strategies are generated by randomly assigning half of the stocks to a "low" portfolio and the other half to a "high" portfolio at the end of every December. Then, I randomly assigned each assets' *i* rank zl_i (zh_i) in the low (high) portfolio. The weight of an asset in a portfolio depends on its rank (see Section 2.2). I do this for data from December 1972 to December 2014, which means I generate monthly data on these random portfolios from January 1973 to December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage.

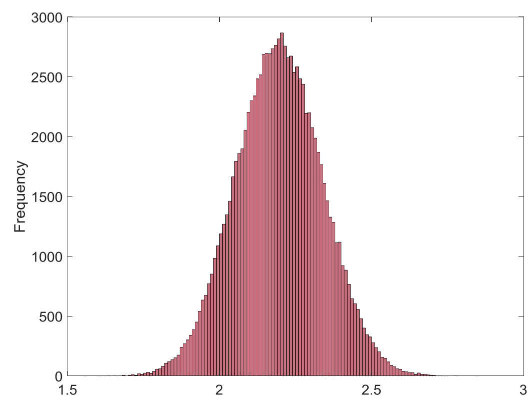
a) Sharpe ratio



c) Carhart's alpha t-statistic



b) CAPM's alpha t-statistic



d) FF5's alpha t-statistic

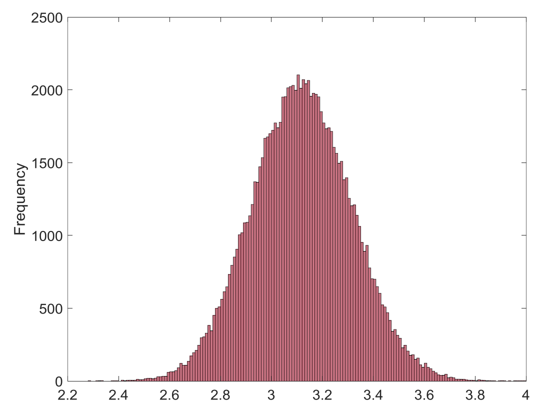
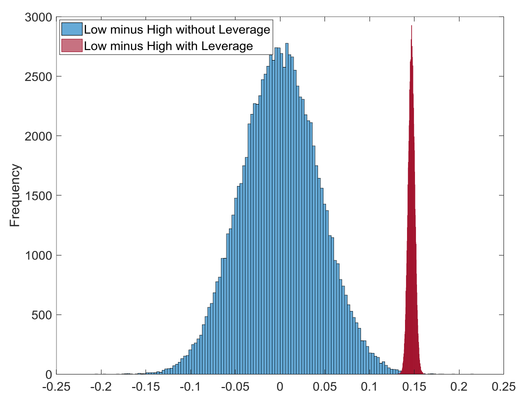


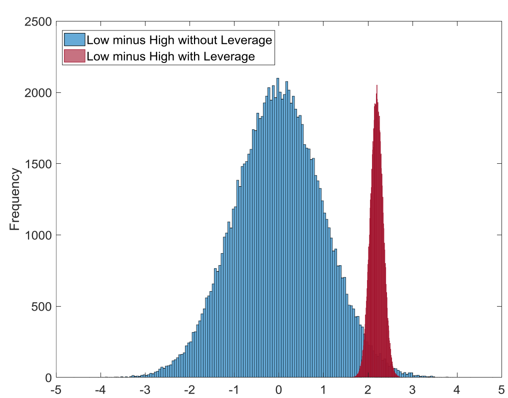
Figure 3: Sharpe ratios and abnormal returns distribution's comparison between BAB and unlevered BAB strategies

This figure presents the empirical distribution of different performance metrics' calculated using 100,000 simulated strategies. Each panel plots the empirical distributions of two simulated strategies: a long-short strategy with leverage (purple) and a long-short strategy without leverage (blue). The performance metrics are the Sharpe Ratio [Panel (a)] and the heteroskedastic robust t-statistics generated by regressing each simulated strategy on the following three models: CAPM, Carhart, and FF5 [Panels (c) to (d)]. The simulated strategies are generated by randomly assigning half of the stocks to a "low" portfolio and the other half to a "high" portfolio at the end of every December. Then, I randomly assigned each assets' *i* rank zl_i (zh_i) in the low (high) portfolio. The weight of an asset in a portfolio depends on its rank (see Section 2.2). I do this from December 1972 to December 2014, which means I generate monthly data on these random portfolios from January 1973 to December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage.

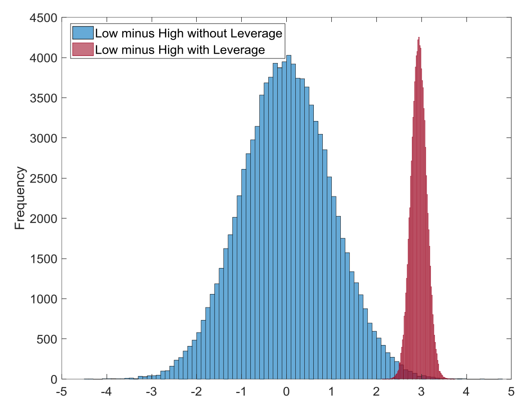
a) Sharpe ratio



b) CAPM's alpha t-statistic



c) Carhart's alpha t-statistic



d) FF5's alpha t-statistic

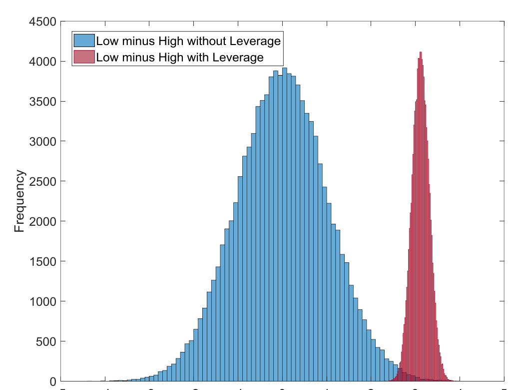
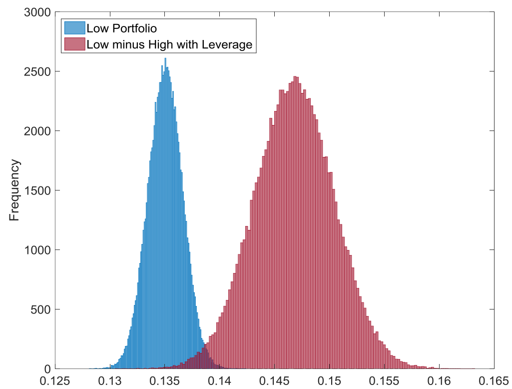


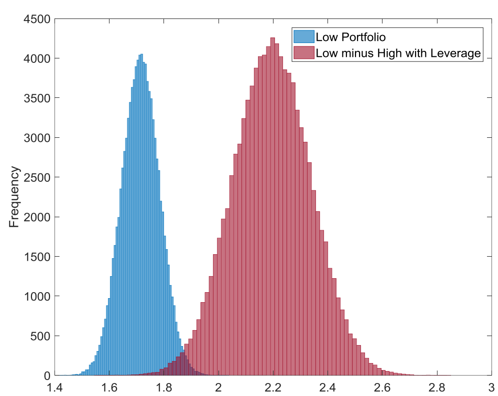
Figure 4: Sharpe ratios and abnormal returns distribution's comparison between the BAB strategy and the excess return of the random low portfolio

This figure presents the empirical distribution of different performance metrics' calculated using 100,000 simulated strategies. Each panel plots two empirical distributions: one for the long-short strategy with leverage (purple) and one for the long portfolio (low portfolio) used to construct the levered strategy (blue). The performance metrics are the Sharpe Ratio [Panel (a)] and the heteroskedastic robust t-statistics generated by regressing each simulated strategy on the following three models: CAPM, Carhart, and FF5 [Panels (c) to (d)]. The simulated strategies are generated by randomly assigning half of the stocks to a "low" portfolio and the other half to a "high" portfolio at the end of every December. Then, I randomly assigned each assets' *i* rank zl_i (zh_i) in the low (high) portfolio. The weight of an asset in a portfolio depends on its rank (see Section 2.2). I do this for data from December 1972 to December 2014, which means I generate monthly data on these random portfolios from January 1973 to December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, and FF5 models comes from Kenneth French's webpage.

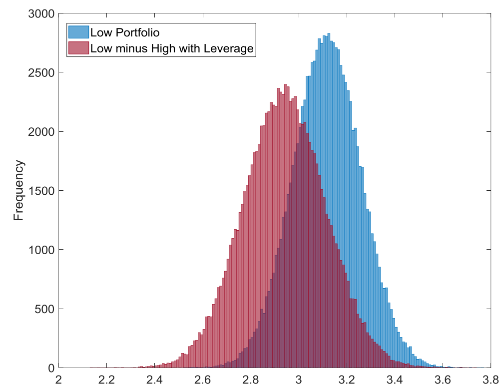
a) Sharpe ratio



b) CAPM's alpha t-statistic



c) Carhart's alpha t-statistic



d) FF5's alpha t-statistic