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Portfolio Sorting by Leverage Ratio and Validation in American Stock Market

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ABSTRACT
The stock market has high risks. The purpose of this project is to sort five different portfolios from all stocks in S&P 500 by the leverage ratio, then perform both time-series and cross-sectional regression on each of the portfolios to find anomalies of pricing, also test whether to choose risk-premium or hedging strategy, and finally build both an out-performing strategy and a long-short strategy. Putting more stocks into the portfolio can help analysts carry out comprehensive analysis on different situations, periods, and types of investment portfolio, so as to disperse risks, in order to ensure the diversity of portfolio and a lower risk.

Keywords: Stock Market, Leverage Ratio Sorting, Time-Series Regression, Cross-Sectional Regression, Long-Short Strategy

Introduction
Currently, investors in stock market are interested in choosing preferrable portfolios to diversify the risk. Therefore, the research on portfolio sorting naturally focuses on the factors for portfolio sorting, and the pricing anomalies in portfolios, and how to build appropriate investment strategies based on the results of these tests.

Leverage ratio here used in our project is defined by the ratio of total debt to the total asset, also called debt-to-asset ratio, which measures the indebtedness of an enterprise. Actually, an appropriate indebtedness can promote a company's profitability. If a company is in no debt, in most cases, it won't gain much profit either. And importantly, the profitability of an enterprise is directly related to the return of the stock it issues. The primary assumption for this paper is that the portfolios consisting by stocks of high leverage ratios tend to be underpriced, while those with lower leverage ratios will be overpriced.

The paper is organized as follows. Section 2 shows the theoretical background for the research conducted in this paper. Section 3 makes a brief review on the literatures referenced in this paper. Section 4 explains the methodology taken in this paper. Section 5 describes the key data used in the project and how we cleansed it. Section 6 presents the time-series asset pricing results that demonstrates the significant risk premia (alpha) caused by leverage ratios. Section 7 validates the results in section 6 and makes risk-premium hypothesis for section 8. Section 8 shows two different strategies built by us. And finally, section 9 concludes the paper.

Theoretical Background
Based on the previous works by Campbell, the main focus of asset pricing is the combination of theoretical and empirical work [1]. Theorists create models that can be scientifically tested, while researchers provide evidence of 'puzzles' - facts that do not align with existing theories, which in turn inspires the creation of new theories. This process is a regular part of the advancement of any field of study. Asset pricing, along with economics in general, encounters a particular challenge where data is naturally generated rather than through controlled experiments, meaning researchers have no control over the amount of data or the random events that impact the data.

Portfolio sorting is a key step for asset pricing. According to the research by Berk, the practice of categorizing stocks into groups for the purpose of testing asset pricing theories originated with the initial tests of the Capital Asset Pricing Model (CAPM) [2,3]. While the loss of information resulting from the categorization process has long been recognized, only recently have researchers started to formally examine the theoretical foundation for conducting such categorizations [4]. In the study by Lo and MacKinlay, they highlighted that if the categorization were based on a variable that is only empirically correlated with returns or a variable measured within the sample, the test would be subject to a bias caused by examining too much data [5]. Liang argued that even when the categorization is based on a variable estimated using past data, errors in measuring this variable can lead to incorrect conclusions [6].

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Literature Review

Portfolio Sorting by Leverage Ratio

From the previous work by Zhou and Palomar, the heuristic quintile portfolio is adopted by this paper [7]. The main idea of heuristic quintile portfolio method by leverage ratio is to separate all the stocks into five different portfolios with the leverage ratios from low too high for all the periods. Due to the distribution of the stocks' leverage ratios in this paper, the stocks are separated into five portfolios based on some of the deciles of their leverage ratios.

Time-Series Regression

The papers by Chiah et al. and Foye introduced the Fama-French models [8,9]. There are three main types of Fama-French time-series regression models: the market model (MM), the Fama-French 3 factors model, and the Fama-French 5 factors model. All the three models contain the monthly market excess return (MktRF) as the explanatory variable, for the Fama-French 3 factors model, SMB (small minus big) and HML (high minus low) are added into the set of explanatory variables. And based on the Fama-French 3 factors model, RMW (robust minus weak) and CMA (conservative minus aggressive) are included, which composes the Fama-French 5 factors model.

Cross-Sectional Fama-MacBeth (FM) Regression

According to the research conducted by Pasquariello the cross-sectional Fama-MacBeth regression can be performed to validate the Fama-French time-series models [10]. The Fama-French factors have positive correlation with the return of stocks when the corresponding lambda coefficients are greater than 0, otherwise, the correlation becomes negative.

Out-Performance and Long-Short Strategies

The works by Meade and Beasley Leibowitz, Emrich and Bova inspire the idea of building both an out-performance and long-short strategy [11,12]. For the out-performance strategy, all the portfolios should have a positive proportion, and the portfolio with the best performance will make up for the highest weight. While for the long-short strategy, short-selling is allowed, which is to say that negative proportions are accepted.

Methodology Framework

Time-Series Regression

Firstly, a market model (MM) is built for each portfolio:

$$\gamma_{it}=\alpha_i+\beta_{MKtRF,i}\,MktRF_t+\varepsilon_{it};i=low,2,3,4,high;t=1,\dots,359$$

Next, for all the five portfolios, a Fama-French 3 factor model is built on each of them:

$$\gamma_{it}=\alpha_{3i}+\beta_{MKtRF,i}MktRF_t+\beta_{SMB,i}SMB_t+\beta_{HML,i}HML_t+\varepsilon_{it};i=low,2,3,4,high;\ t=1,\dots,359$$

Similarly, a Fama-French 5 factor model is also built:

$$\gamma_{it}=\alpha_{5i}+\beta_{MKtRF,i}MktRF_t+\beta_{SMB,i}SMB_t+\beta_{HML,i}HML_t+\beta_{RMW,i}RMW_t+\beta_{CMA,i}CMA_t+\varepsilon_{it};i=low,2,3,4,high;t=1,\dots,359$$

To estimate the α and β coefficients in each of these three regression models, the least squares method will be used:

1. Rewrite the regression model as the matrix form: $\boldsymbol{y}=\boldsymbol{X\beta}+\varepsilon$, where

$X=\begin{pmatrix}1 & x_{11} & \cdots & x_{k1}\\ \vdots & \vdots & \ddots & \vdots\\ 1 & x_{1,359} & \cdots & x_{k,359}\end{pmatrix}$ x_{kt} means the value of the k^{th} Fama-French factor in the t^{th} month, and

$y=\begin{pmatrix}r_{i1}\\ \vdots\\ r_{i,359}\end{pmatrix}$, $\boldsymbol{\beta}=\begin{pmatrix}\alpha_i\\ \beta_{1i}\\ \vdots\\ \beta_{ki}\end{pmatrix}$, β_{ki} is the beta coefficient for the kth Fama-French factor in the model, and definitely, $\boldsymbol{\varepsilon}=\begin{pmatrix}\varepsilon_{i1}\\ \vdots\\ \varepsilon_{i,359}\end{pmatrix}$.

2. The best estimator for $\boldsymbol{\beta}$ is $b=(X'X)^{-1}X'y$

The higher the alpha coefficient for a portfolio, the more this portfolio is underpriced.

Cross-Sectional Fama-MacBeth (FM) Regression

A cross-sectional Fama-MacBeth (FM) regression is performed on each portfolio:

$$\bar{\gamma}=\lambda_{Mkt}\beta_{MKtRF,i}+\lambda_{SMB}\beta_{SMB,i}+\lambda_{HML}\beta_{HML,i};i=low,2,3,4,high$$

Here the beta coefficients are already estimated in the Fama-French 3 factors model, to estimate the lambda coefficients, the procedures are similar:

1. Rewrite the regression model as the matrix form: $\bar{\boldsymbol{\gamma}}=\hat{\boldsymbol{\beta}}\boldsymbol{\lambda}$, *where* $\hat{\boldsymbol{\beta}}=$

$\begin{pmatrix}\beta_{MKT,low} & \beta_{SMB,low} & \beta_{HML,low}\\ \vdots & \ddots & \vdots\\ \beta_{MKT,high} & \cdots & \beta_{HML,high}\end{pmatrix}$, $\bar{\boldsymbol{r}}=$

$\begin{pmatrix}\bar{r}_{low}\\ \vdots\\ \bar{r}_{high}\end{pmatrix}$, and $\boldsymbol{\lambda}=\begin{pmatrix}\lambda_{Mkt}\\ \lambda_{SMB}\\ \lambda_{HML}\end{pmatrix}$.

2. The best estimator for $\boldsymbol{\lambda}$ is $\hat{\boldsymbol{\lambda}}=(\hat{\boldsymbol{\beta}}'\hat{\boldsymbol{\beta}})^{-1}\hat{\boldsymbol{\beta}}'\bar{\boldsymbol{r}}$.

Out-Performance and Long-Short Strategies

The covariance between the monthly excess returns of each portfolio is calculated by:

$$\sigma_{ij}=\frac{\sum_{t=1}^{359}(r_{it}-\bar{r}_i)(r_{jt}-\bar{r}_j)}{358};i,j=low,2,3,4,high$$

Based on the covariance results and basic characteristics of each portfolio, the out-performance and long-short strategy can be built for further analysis. The aim of both strategies is to maximize their Sharpe ratios. According to the achievements from Markowitz and Sharpe the target function can be expressed as: [13,14]

$$\max_{\omega} S=\frac{\sum_{i=low}^{high}\omega_i\bar{r}_i}{\sum_{i=low}^{high}\omega_i^2\sigma_i^2+\sum_{j=low}^{high}\sum_{i=low}^{high}\omega_i\omega_j\sigma_{ij}};i,j=low,2,3,4,high;i\neq j$$

Here ω is the proportion of each portfolio in both strategies, and

$$\sigma_i^2 = \frac{\sum_{t=1}^{359}(r_{it}-\bar{r}_i)^2}{358}$$

represents the variance of the monthly excess return rate for the i^{th} portfolio. The difference point is that for the out-performance strategy, ω must be between 0 and 1, while this may be negative for long-short strategy.

Data and Initial Analysis

The dataset for this paper contains the monthly excess return rates and leverage ratios of all stocks in S&P 500 from December 1,992 to November 2,022, and the Fama-French-5-factor data. The portfolio sorting is conducted based on the monthly leverage ratios, which separated all the stocks to 5 portfolios. The steps in details are: 1. The leverage ratios are shifted by one month in order to make them correspond to the right month periods, 2. All stocks in S&P 500 are separated in the next month into five different portfolios: low, 2, 3, 4, high by the fiftieth, sixtieth, seventieth and eightieth percentiles of leverage ratios in the last month, then the monthly average leverage ratios and return rates of each portfolio are calculated, 3. Step 2 is repeated for 358 times, finally the average monthly returns and leverage ratios of each portfolio from January 1,993 to November 2,022 are got. In this paper, the weights of each stock in each portfolio are treated to be equal to each other. The return rate and leverage ratio of each portfolio in each month can be expressed by:

$$r_{it} = \frac{\sum_{s=1}^{N} r_{st}}{N}; \quad i=low,2,3,4,high;\ t=1,\ldots,359$$

$$LEV_{it} = \frac{\sum_{s=1}^{N} LEV_{st}}{N}; \quad i=low,2,3,4,high;\ t=1,\ldots,359$$

In addition, the leverage ratio of a portfolio in a specific month is re-defined as 0 if it doesn't contain any stocks due to the separation in step 2.

Time-Series Regression Results

As the monthly return rates for all the 5 portfolios are achieved, firstly a market model (MM) regression is run, including the leverage ratio of each portfolio and MktRF as the explanatory variables, in order to calculate the leverage beta ratios. Then the tests on both Fama-French 3 and 5 factors are conducted to compare the Jensen's alphas, which is an index for the measurement of the unexpected return of a portfolio. For the Fama-French 3 (FF3) model, the monthly return is set as the dependent variable, while the MktRF, SMB and HML of each portfolio become the explanatory variables, then conduct a linear regression. For the Fama-French 5 (FF5) model, the procedure is similar, the only difference is that RMW and CMA are added to the explanatory variables. The results for these two regressions are listed in Table 1.

Table 1: shows Univariate Portfolios Sorted by Leverage Ratio

Port-folio	Leverage Ratio	Excess Return	α	α_3	α_5
Low	0.2695	0.0090 (3.7150)	0.0032 (2.1698)	0.0033 (2.2969)	0.0031 (2.0876)
2	0.3682	0.0084 (3.8730)	0.0032 (2.4283)	0.0027 (2.1401)	0.0014 (1.0571)
3	0.4478	0.0082 (3.9585)	0.0036 (2.5552)	0.0031 (2.2884)	0.0013 (0.9911)
4	0.5288	0.0063 (2.9370)	0.0018 (1.1455)	0.0010 (0.7020)	-0.0011 (-0.7417)
High	0.8386	0.0124 (4.1488)	0.0046 (3.0878)	0.0033 (2.8492)	0.0030 (2.4735)
High-Low		0.0034 (1.6049)	0.0014 (0.718)	4.4720e -05 (0.0261)	-1.0322e -04 (-0578)

Table 1 presents the univariate portfolio results using leverage ratios. For each month, five portfolios are formed by sorting individual stocks based on leverage ratios. The low-leverage portfolio contains stocks with the lowest leverage ratios during the last month, and the high-leverage portfolio contains stocks with the highest leverage ratios. The first column shows the average leverage ratio for each portfolio using full-sample breakpoints. The second column presents the average value-weighted excess return and associated t-statistics for each portfolio. The last row reports these for the high-minus-low portfolio (highest-leverage portfolio – lowest-leverage portfolio for excess return and alpha).

From the first column, it shows that the average leverage ratios vary drastically from low-leverage portfolio to high-leverage portfolio. The average leverage ratio rises sharply from 0.2695 to 0.8386. Stocks in the high-leverage portfolio, have mean leverage ratios close to 1.

The third column presents that next-month average excess returns generally increases as the leverage beta ratio moving from low to high. The average excess return reaches to the maximum point across all the 5 portfolios at 0.0124 for the high-leverage portfolio, while the lowest falls to 0.0063 for portfolio 4. The average return difference between highest and lowest is 0.34% per month with a Newey and West t-statistic of 1.6049 [15].

The remaining three columns in Table 1 present the magnitude and statistical significance of risk-adjusted returns (alphas) from two models: (1) the market model (MM) (α), (2) the Fama-French three factor model (α_3), and (3) the Fama-French five factor model (α_5). The mean value-weighted alpha arrives to the valley floor for portfolio 4, and generally gets to the highest level for the high-leverage portfolio. The high-minus-low portfolio mean alpha keeps on being insignificant for all of the three models, which means that there is no obvious difference between the Jenson's alphas for both the low and high-leverage portfolios. So, such results correspond to the preliminary assumption.

Cross-Sectional Fama-MacBeth (FM) Regression Results

In this section, the results derived in the previous section are validated. The beta coefficients of FF3 model in the four portfolios sorted by leverage ratio in section 3 are shown in Table 2.

Table 2: shows Beta Ratios of FF3 Model in Portfolios Sorted by Leverage Ratio

Portfolio	$\beta_{3,MKtRF}$	$\beta_{3,SMB}$	$\beta_{3,HML}$
Low	0.7961 (24.5430)	0.2134 (4.5349)	-0.0599 (-1.4134)
2	0.7256 (25.0612)	0.1444 (3.4375)	0.2002 (5.2916)
3	0.6575 (21.2047)	0.0757 (1.6838)	0.1796 (4.4330)
4	0.6645 (20.1457)	0.0023 (0.0474)	0.3081 (7.1474)
High	1.1272 (42.5225)	0.0773 (2.0100)	0.5303 (15.3082)

Comprehensively, by Table 1 and 2, we conducted a cross-sectional FM (Fama-Macbeth) regression. The results for this cross-sectional FM regression are shown in Table 3.

Table 3: shows Cross-Sectional FM λ

FF3 Factor	λ
MktRF	0.0091
SMB	0.0103
HML	0.0025

From Table 3, it can be observed that all the beta coefficients of Fama-French 3 factors are positively proportional to the mean excess return of each portfolio, which validates the results in section 3. So, the analysis results can be used to build the proper investment strategies, corresponding to the hedging hypothesis.

Out-Performance and Long-Short Strategies VS S&P 500

This paper also builds up a covariance table of the monthly excess return rates between each of the 5 portfolios, which is shown in Table 4.

Table 4: shows Covariance Table

	Low	2	3	4	High
Low	0.002 119	0.001 727	0.001 548	0.001 464	0.001 876
2	0.001 727	0.001 686	0.001 486	0.001 496	0.001 893
3	0.001 548	0.001 486	0.001 532	0.001 373	0.0017
4	0.001 464	0.001 496	0.001 373	0.001 646	0.001 783
High	0.001 876	0.001 893	0.0017	0.001 783	0.003 188

According to Table 4, and previous results, an out-performance strategy is built up firstly, which is under the hedging hypothesis. The out-performance strategy consists of 60% weight in the high-leverage portfolio, and 10% weights in each of the other portfolios. Next, a long-short strategy is built up. According to Table 1, only portfolio 4 is relatively overpriced, and the high-leverage portfolio has the highest degree of being underpriced. So, a long position is taken on it, and all others are sold short. By the famous 130/30 theorem in long-short strategy, the weight for the high-leverage portfolio is set as 130%, while -7.5% for other four portfolios. The details of weights of each portfolio in these two strategies are shown in Table 5.

Table 5: shows Weights of Each Portfolio in both Out-Performance and Long-Short Strategy

Portfolio	Out-Performance	Long-Short Strategy
Low	10%	-7.5%
2	10%	-7.5%
3	10%	-7.5%
4	10%	-7.5%
High	60%	130%

Combined Table 1, 4 and 5, the annualized excess return rates, standard deviations, and Sharpe ratio of out-performance and long-short strategy, also with the entire S&P 500 are calculated.

Table 6: shows Expected Profitability and Risk of both Out-Performance and Long-Short Strategy

	Annualized Excess Return Rate	Annualized Standard Deviation	Annualized Sharpe Ratio
Out-Performance	12.75%	16.50%	0.77
Long-Short	16.44%	22.22%	0.74
S&P 500	6.44%	14.96%	0.43

The accumulative return from January, 1,993 to a certain period m is computed by:

$$R_m = \prod_{t=1}^{m}(1 + r_t) - 1$$

The trend graph of monthly and accumulative excess return rates of out-performance strategy, long-short strategy, and S&P 500 are also plotted, where the monthly return is set as the primary vertical axis, while the accumulative return becomes the secondary vertical axis, and the date is the horizontal axis, as it shows in Figure 1.

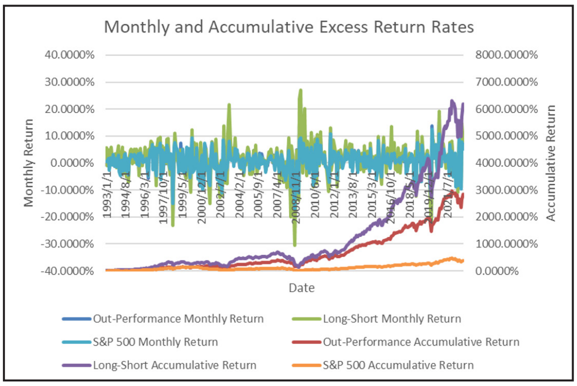

Figure 1: shows Monthly and Accumulated Excess Return Rates

By Table 6 and Figure 1, it can be observed that while the out-performance strategy has the highest Sharpe ratio, the one for the long-short strategy is very close to it over the past 30 years. Besides, the monthly excess return rate of the two strategies and S&P 500 are almost the same, but investors may gain the highest accumulative excess return if they keep on investing on long-short strategy from the beginning of the research period [15-19]..

Conclusion

This paper investigates the role of leverage ratio in asset pricing. The results of the research verify the primary assumption that the portfolios of high leverage ratios tend to be underpriced, while those of low leverage ratios have the tendency of being overpriced. Based on the research, both an out-performance strategy and a long-short strategy are built. Here in this paper, the out-performance strategy has the highest Sharpe ratio, but the one of the long-short strategy is almost equivalent to it, besides, the accumulative excess return rate for the out-performance strategy is the highest. For investors, the recommendation is to take long-short strategy based on pricing anomalies.

Appendix

```
# loading datafiles
load predata.mat
load FamaFrench5Factors.mat

# delaying the leverage ratio by one grid
stk_axis = unique(predata.PERMNO);
for i = 1 : length(stk_axis)
    index_stk = find(predata.PERMNO == stk_axis(i));
    databystk = predata(index_stk, : );
    databystk.Lev = circshift(databystk.LeverageRatio, 1);
    predata(index_stk, 2) = databystk( : , 2);
end

# rolling grouping, calculating the average leverage ratios and return rates
time_axis = unique(predata.Date);

lev = [];
ret = [];

for i = 1 : length(time_axis) - 1
    index_t = find(predata.Date == time_axis(i+1));
    data_now = predata(index_t, : );

    temp = table2array(data_now( : , 5));
    a = prctile(temp, 60);
    b = prctile(temp, 70);
    c = prctile(temp, 80);
    d = prctile(temp, 90);

    tier1 = find(data_now.LeverageRatio < a);
    tier2 = find(data_now.LeverageRatio >= a & data_now.LeverageRatio < b);
    tier3 = find(data_now.LeverageRatio >= b & data_now.LeverageRatio < c);
    tier4 = find(data_now.LeverageRatio >= c & data_now.LeverageRatio < d);
    tier5 = find(data_now.LeverageRatio >= d);

    L_tier1 = mean(table2array(data_now(tier1, 5)));
    L_tier2 = mean(table2array(data_now(tier2, 5)));
    L_tier3 = mean(table2array(data_now(tier3, 5)));
    L_tier4 = mean(table2array(data_now(tier4, 5)));
    L_tier5 = mean(table2array(data_now(tier5, 5)));
    R_tier1 = mean(table2array(data_now(tier1, 4)));
    R_tier2 = mean(table2array(data_now(tier2, 4)));
R_tier3 = mean(table2array(data_now(tier3, 4))); R_tier4 = mean(table2array(data_now(tier4, 4))); R_tier5 = mean(table2array(data_now(tier5, 4)));

    lev(i, : ) = [L_tier1 L_tier2 L_tier3 L_tier4 L_tier5 ];
    ret(i, : ) = [R_tier1 R_tier2 R_tier3 R_tier4 R_tier5 ];

end

# calculating the excess return rates
Y_1 = ret( : , 1);
Y_2 = ret( : , 2);
Y_3 = ret( : , 3);
Y_4 = ret( : , 4);
Y_5 = ret( : , 5);

Y_1 = Y_1 - FamaFrench5Factors.Rf(2 : 360);
Y_2 = Y_2 - FamaFrench5Factors.Rf(2 : 360);
Y_3 = Y_3 - FamaFrench5Factors.Rf(2 : 360);
Y_4 = Y_4 - FamaFrench5Factors.Rf(2 : 360);
Y_5 = Y_5 - FamaFrench5Factors.Rf(2 : 360);

# calculating the mean excess return rates and their t-values
mean_ret_1 = mean(Y_1);
mean_ret_2 = mean(Y_2);
mean_ret_3 = mean(Y_3);
mean_ret_4 = mean(Y_4);
mean_ret_5 = mean(Y_5);

mean_ret = [mean_ret_1 mean_ret_2 mean_ret_3 mean_ret_4 mean_ret_5];

[h1, p1, ci1, stats1] = ttest(Y_1);
[h2, p2, ci2, stats2] = ttest(Y_2);
[h3, p3, ci3, stats3] = ttest(Y_3);
[h4, p4, ci4, stats4] = ttest(Y_4);
[h5, p5, ci5, stats5] = ttest(Y_5);
[h, p, ci, stats] = ttest(Y_5 - Y_1);
```

```
# calculating the mean leverage ratios
L_1 = lev( : , 1);
L_2 = lev( : , 2);
L_3 = lev( : , 3);
L_4 = lev( : , 4);
L_5 = lev( : , 5);

mean_lev = [mean(L_1) mean(L_2) mean(L_3) mean(L_4)
mean(L_5)];

# calculating the Jenson’s alpha for the market model and the
t-value
X_MM = FamaFrench5Factors.MktRF(2 : 360);
stats_MM_1 = regstats(Y_1, X_MM, “linear”, “tstat”);
stats_MM_2 = regstats(Y_2, X_MM, “linear”, “tstat”);
stats_MM_3 = regstats(Y_3, X_MM, “linear”, “tstat”);
stats_MM_4 = regstats(Y_4, X_MM, “linear”, “tstat”);
stats_MM_5 = regstats(Y_5, X_MM, “linear”, “tstat”);

stats_a = regstats(Y_5 -Y_1, X_MM, “linear”, “tstat”);

# calculating the Jenson’s alpha for the Fama-French 3 factors
model and the t-value
X_FF3 = [FamaFrench5Factors.MktRF(2 : 360)
FamaFrench5Factors.SMB(2 : 360) FamaFrench5Factors.
HML(2 : 360)];
stats_FF3_1 = regstats(Y_1, X_FF3, “linear”, “tstat”);
stats_FF3_2 = regstats(Y_2, X_FF3, “linear”, “tstat”);
stats_FF3_3 = regstats(Y_3, X_FF3, “linear”, “tstat”);
stats_FF3_4 = regstats(Y_4, X_FF3, “linear”, “tstat”);
stats_FF3_5 = regstats(Y_5, X_FF3, “linear”, “tstat”);

stats_a3 = regstats(Y_5 -Y_1, X_FF3, “linear”, “tstat”);

beta_all_FF3 = [stats_FF3_1.tstat.beta stats_FF3_2.tstat.beta
stats_FF3_3.tstat.beta stats_FF3_4.tstat.beta stats_FF3_5.tstat.
beta];
beta_FF3 = beta_all_FF3(2 : 4, : );

# calculating the Jenson’s alpha for the Fama-French 5 factors
model and the t-value
X_FF5 = [FamaFrench5Factors.MktRF(2 : 360)
FamaFrench5Factors.SMB(2 : 360) FamaFrench5Factors.
HML(2 : 360) FamaFrench5Factors.RMW(2 : 360)
FamaFrench5Factors.CMA(2 : 360)];
stats_FF5_1 = regstats(Y_1, X_FF5, “linear”, “tstat”);
stats_FF5_2 = regstats(Y_2, X_FF5, “linear”, “tstat”);
stats_FF5_3 = regstats(Y_3, X_FF5, “linear”, “tstat”);
stats_FF5_4 = regstats(Y_4, X_FF5, “linear”, “tstat”);
stats_FF5_5 = regstats(Y_5, X_FF5, “linear”, “tstat”);

stats_a5 = regstats(Y_5 -Y_1, X_FF5, “linear”, “tstat”);

beta_all_FF5 = [stats_FF5_1.tstat.beta stats_FF5_2.tstat.beta
stats_FF5_3.tstat.beta stats_FF5_4.tstat.beta stats_FF5_5.tstat.
beta];
beta_FF5 = beta_all_FF5(2 : 6, : );

# calculating the cross-sectional lambda
lambda_FF3 = inv(beta_FF3 * beta_FF3’) * beta_FF3 * mean_
ret’;
```

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