# Mandatory Assignment 2

Asbjørn Fyhn & Emil Beckett Kolko

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**Introduction**

Jegadeesh and Titman (1993) documented that a portfolio that goes long high return stocks and short low return stocks over the past 3 to 12 months earn abnormal profits the following year. This phenomenon is known as the medium-term momentum effect. In this assignment, we first investigate this effect by estimating the returns of a long/short momentum portfolio by OLS. Next, we explore predictions of cross-sectional stock returns using only past returns as predictors. This analysis is conducted through a machine learning framework using ridge regression. Instead of the positive correlation between last year's and future returns found in Jegadeesh and Titman (1993), we find a negative correlation. Therefore, we conclude that a portfolio that goes long low return stocks and short high return stocks over the past 12 months earn abnormal profits.

**Exercise 1 and 2:**

We load the "tidy_finance_python.sqlite" database and read in selected variables from the tables "crsp_monthly" and "factors_ff3_monthly".

When computing the momentum we use the market capitalization as opposed to the stock price. The benefit of doing so, is that our computations are not affected by events that increase or decrease the number of outstanding stocks such as stock issuances or buybacks. If we had used the stock price in our computations as opposed to the market capitalization, such events would have artificially increased or decreased our calculated momentum.

After completing exercise 1 and 2 our dataframe looks like this:

Table 1: Three random rows of data from the tidy_finance_python.sqlite database

| permno | month | ret_excess | mktcap | mktcap_lag | mktcap_lag_12 | Mom_12 |
|---|---|---|---|---|---|---|
| 10028 | 1993-03-01 | -0.10 | 6.33 | 7.03 | 15.26 | -53.91 |
| 10028 | 1993-04-01 | 0.39 | 8.79 | 6.33 | 12.66 | -49.99 |
| 10028 | 1993-05-01 | 0.20 | 10.55 | 8.79 | 10.06 | -12.58 |

Where "permno" is the unique security identifier, "ret_excess" is the monthly return above the risk free rate (where -0.1=-10%), the "mktcap" variables are in USD millions, and "Mom_12" is the 12-month momentum in percentage terms.

**Exercise 3:**

The equal-weighted average values of the 12-month momentum and market capitalization is shown in Table 2 below:

Table 2: Average momentum and average market cap

Table 2

| Momentum decile | Average momentum | Average market cap |
|---|---|---|
| 1 | -61.82 | 376.38 |
| 2 | -35.18 | 971.25 |
| 3 | -20.36 | 1650.68 |
| 4 | -9.18 | 2348.25 |
| 5 | 0.44 | 2972.50 |
| 6 | 10.00 | 3354.10 |
| 7 | 21.01 | 3457.84 |
| 8 | 35.78 | 3092.28 |
| 9 | 61.34 | 2257.36 |
| 10 | 208.71 | 1370.94 |

Furthermore, we present the average excess return and the CAPM alpha for the ten momentum-sorted portfolios in table 2. The excess returns are reported in the "factors_ff3_monthly" dataset and the CAPM alphas are estimated with OLS from the CAPM equation:

$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \epsilon_{i,t}$

The null-hypothesis is that alpha is zero and the alternative hypothesis is that alpha is different from zero:

$H_0 : \alpha_i = 0$

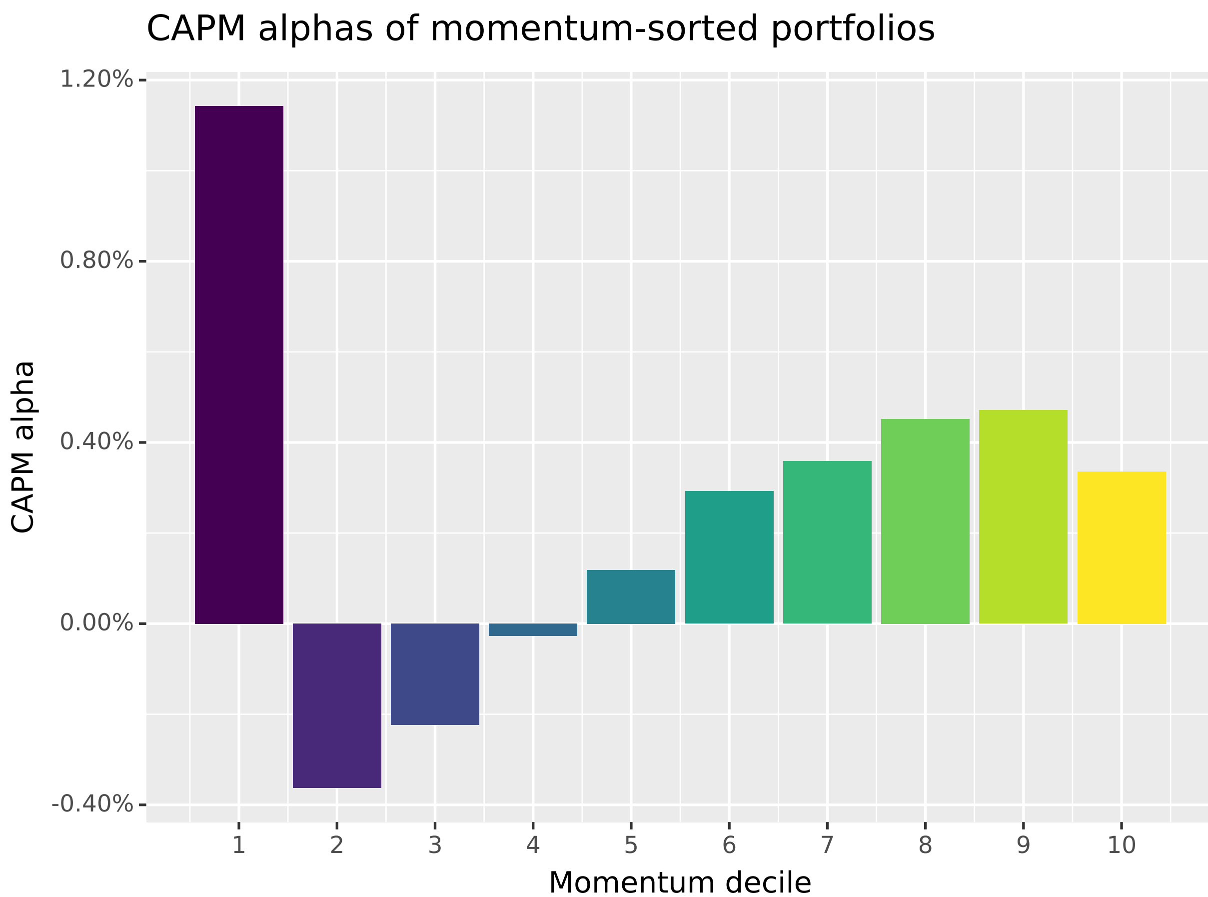
$H_A : \alpha_i \neq 0$

Table 3: Alphas across the ten portfolios

Table 3

| Momentum decile | Excess return | Alpha | t-statistic | p-value |
|---|---|---|---|---|
| 1 | 0.0477 | 0.0114 | 18.98 | 0.00 |
| 2 | 0.0215 | -0.0036 | -10.57 | 0.00 |
| 3 | 0.0133 | -0.0022 | -8.08 | 0.00 |
| 4 | 0.0126 | -0.0003 | -1.09 | 0.27 |
| 5 | 0.0114 | 0.0012 | 5.35 | 0.00 |
| 6 | 0.0096 | 0.0029 | 13.57 | 0.00 |
| 7 | 0.0129 | 0.0036 | 16.43 | 0.00 |
| 8 | 0.0141 | 0.0045 | 19.34 | 0.00 |
| 9 | 0.0157 | 0.0047 | 17.72 | 0.00 |
| 10 | 0.0309 | 0.0034 | 9.19 | 0.00 |

We see from the t-statistics and p-values, that we can reject the null-hypothosis in all cases except for the portfolio of 4th decile momentum stocks. As such, alpha is significantly different from zero in all other cases. To get a better sense of the distribution of alpha accross the ten portfolios, we present the data in a graph:




We see that the lowest decile stocks offer high alphas compared to the rest of the stocks. We expected the lowest performing stocks to have a negative alpha in accordance with Jegadeesh and Titman (1993). The 2nd and 3rd decile stocks are more aligned with their paper showing negative alphas and the stocks in the 5th decile and up offer positive alphas. These findings represent an imperfection in the market. In the following, we test if we can exploit this imperfection with a momentum strategy that goes long past winners and short past losers.

Specifically, we examine the alpha and beta of a portfolio that shorts the 1st decile portfolio and goes long the 10th decile portfolio. We note that this entails shorting stocks with high alpha to buy stocks with lower alpha, which seems counter-intuitive. We analyze the alpha and beta of this portfolio with t-statistics. Here our hypothesizes are:

$H_0 : \alpha = 0$

$H_0 : \beta = 0$

To compute the Newey-West standard errors we must choose a bandwidth based on lags for the estimation. The choice here is rather arbitrary and not data-driven, but we choose a lag length of

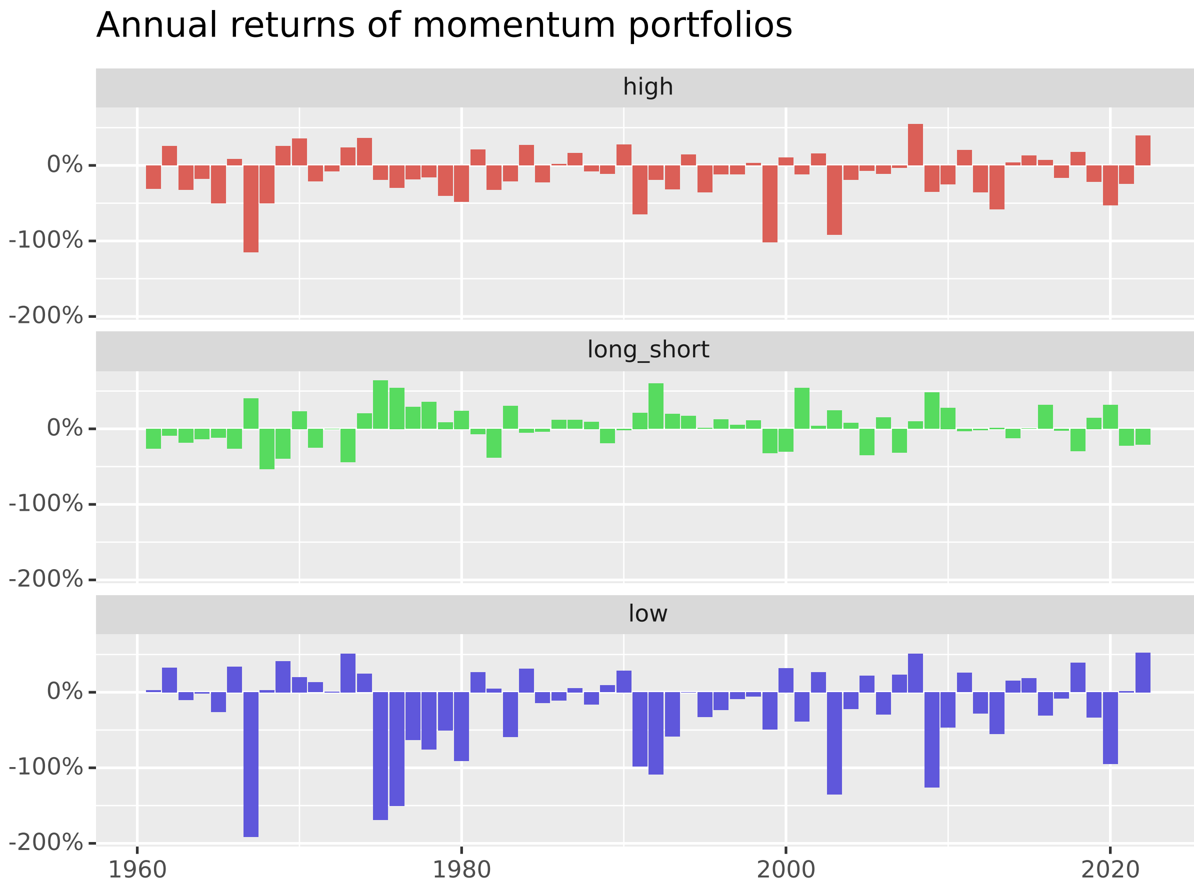
12 months, since that is also the lag length of the momentum stocks. Our results are presented below:

```
OLS Model:
long_short ~ 1 + mkt_excess

Coefficients:
            Estimate  Std. Error  t-Statistic  p-Value
Intercept     -0.002       0.003       -0.907    0.364
mkt_excess    -0.217       0.077       -2.805    0.005

Summary statistics:
- Number of observations: 736
- R-squared: 0.018, Adjusted R-squared: 0.017
- F-statistic: 7.866 on 1 and 734 DF, p-value: 0.005
```

We cannot reject the null hypothesis that the returns, $\alpha$, of the momentum strategy is 0. This finding is in accordance with the CAPM model, that arbitrage strategies are not possible. However, our results deviate from Jegadeesh and Titman (1993) which suggests that it is possible to obtain a positive $\alpha$ with the momentum strategy. The deviation in our results can be explained by the high alphas of portfolio 1, which is not usually observed.

Our results show a significant negative $\beta$, which means the momentum (long/short) portfolio is negatively correlated with the market. This type of portfolio is rare and can be used to reduce the market risk of other investments with positive betas.

To further our understanding of the returns of the portfolio we plot the graph below:




The graphs generally show an expected pattern with both positive and negative returns. All portfolios exhibit autocorrelation in the returns, which further the argument for a momentum portfolio. Interestingly, the momentum long/short portfolio seems to deliver the highest returns even though the two other portfolios have positive alphas.

**Exercise 4** In this exercise, we want to estimate a model where the excess return of a stock is linear dependent on its own 60 lags. The regression model looks as follows:

$r_{i,t+1} 0 \sum_{k=1}^{60} b_k r_{i,t-k} + \sum_{k=1}^{60} c_k r_{i,t-k}^2$

First, we start by cleaning the dataset meaning that we remove the smallest stocks. More precisely, we remove the stocks with the 5% lowest market capitalization.

Next, we demean the dependent variable $r_{i,t+1}$ by month by month subtracting the mean from series. Thus by construction, the mean of the excess return in each month is 0. At the same time, we standardize the lagged excess return by month by month dividing with the standard deviation. In each month, the standard deviation across the firms is one.

The entire dataset has now been cleaning and transformed in such a way that we are ready to take the analysis further. We will estimate regression coefficient using ridge regression. Thus, we will have to choose the hyperparameter, $\alpha$.

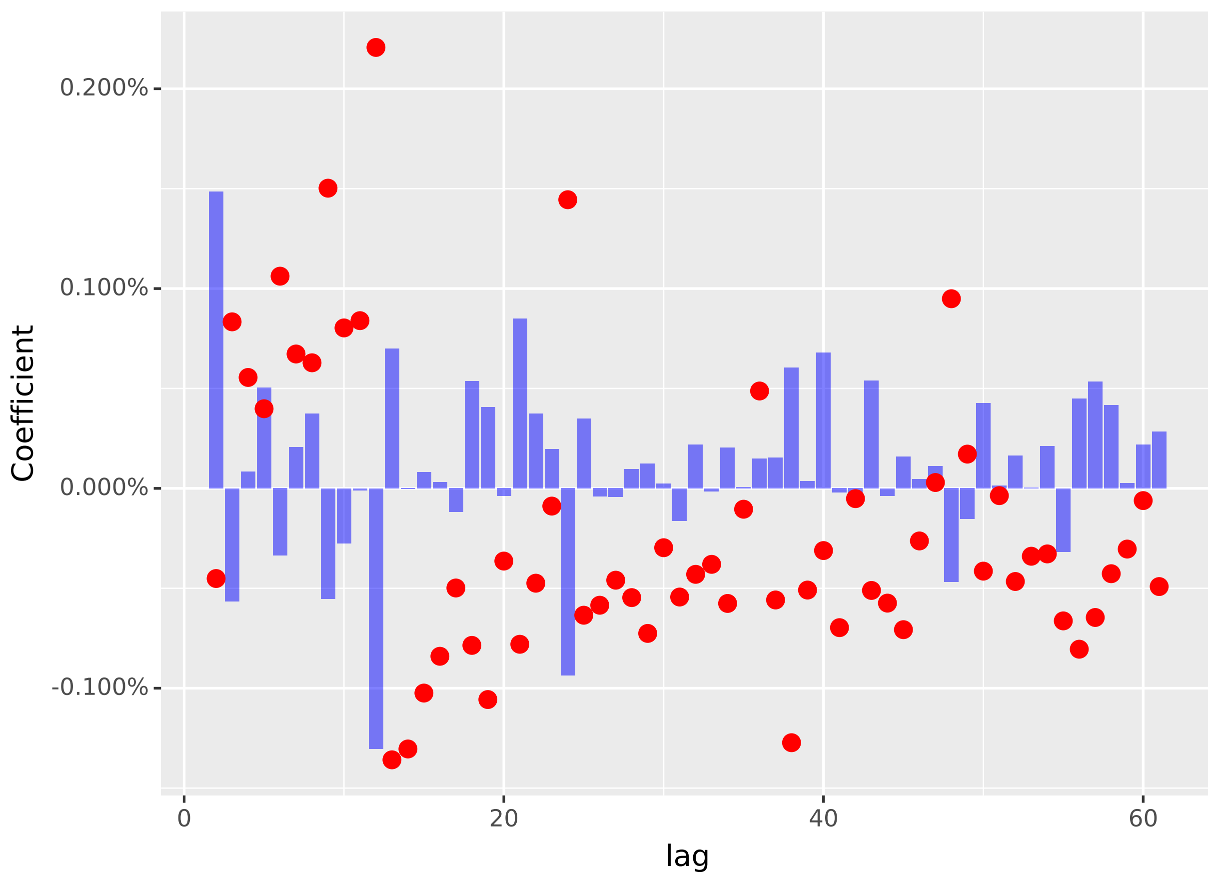
The hyperparameter is chosen by minimizing the estimated mean squared prediction error, MSPE.

$MSPE = E\left(\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_t - y_t)^2\right)$

Before fine tuning the model, we divide our dataset into a training set for hyperparameter selection. Since MSPE can only be estimated, we employ cross-validation. This involves averaging the MSPE across K data folds over a range of hyperparameters. The hyperparameter that yields the lowest MSPE is then selected.

We tune the model over a grid of alphas that goes from 0.0 to 10000.0 with 100 datafolds.

After tuning the model, we set alpha to 0.007




We notice that the coefficient infront of $r_{i,t-k}^2$ seem to be large for $k = 12, 24, 36, 48$. The corresponding lagged not squared excess return are negative. Meaning that the excess returns are predicted to be lower when the excess return same month in the previous years were posive. Based on this analysis, one might suggest to short those stocks that in a certain month previous years experienced positive excess returns.

Table 4

| lag | r | r^2 | lag | r | r^2 | lag | r | r^2 |
|---|---|---|---|---|---|---|---|---|
| 2 | 0.001484 | -0.000451 | 22 | 0.000375 | -0.000474 | 42 | -0.000030 | -0.000051 |
| 3 | -0.000565 | 0.000834 | 23 | 0.000197 | -0.000089 | 43 | 0.000540 | -0.000511 |
| 4 | 0.000084 | 0.000555 | 24 | -0.000937 | 0.001445 | 44 | -0.000037 | -0.000574 |
| 5 | 0.000505 | 0.000399 | 25 | 0.000349 | -0.000635 | 45 | 0.000159 | -0.000707 |
| 6 | -0.000335 | 0.001062 | 26 | -0.000041 | -0.000585 | 46 | 0.000047 | -0.000263 |
| 7 | 0.000206 | 0.000673 | 27 | -0.000043 | -0.000459 | 47 | 0.000112 | 0.000029 |
| 8 | 0.000375 | 0.000629 | 28 | 0.000096 | -0.000547 | 48 | -0.000468 | 0.000949 |
| 9 | -0.000552 | 0.001502 | 29 | 0.000124 | -0.000726 | 49 | -0.000153 | 0.000172 |
| 10 | -0.000275 | 0.000803 | 30 | 0.000023 | -0.000297 | 50 | 0.000427 | -0.000414 |
| 11 | -0.000010 | 0.000839 | 31 | -0.000162 | -0.000544 | 51 | 0.000013 | -0.000036 |
| 12 | -0.001304 | 0.002207 | 32 | 0.000219 | -0.000430 | 52 | 0.000163 | -0.000466 |
| 13 | 0.000700 | -0.001358 | 33 | -0.000014 | -0.000380 | 53 | 0.000005 | -0.000340 |
| 14 | -0.000003 | -0.001304 | 34 | 0.000204 | -0.000576 | 54 | 0.000212 | -0.000328 |
| 15 | 0.000081 | -0.001024 | 35 | 0.000006 | -0.000104 | 55 | -0.000317 | -0.000663 |
| 16 | 0.000032 | -0.000840 | 36 | 0.000148 | 0.000487 | 56 | 0.000449 | -0.000805 |
| 17 | -0.000118 | -0.000498 | 37 | 0.000153 | -0.000558 | 57 | 0.000535 | -0.000646 |
| 18 | 0.000537 | -0.000786 | 38 | 0.000604 | -0.001273 | 58 | 0.000417 | -0.000427 |
| 19 | 0.000406 | -0.001057 | 39 | 0.000035 | -0.000509 | 59 | 0.000026 | -0.000304 |
| 20 | -0.000038 | -0.000364 | 40 | 0.000679 | -0.000311 | 60 | 0.000218 | -0.000061 |
| 21 | 0.000850 | -0.000780 | 41 | -0.000021 | -0.000697 | 61 | 0.000285 | -0.000491 |