**CFM 301 Winter 2024 – Financial Data Analytics**

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**Assignment 3**

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**Report/Summary of conclusions from the code**

**Task 1 – Estimating beta**

*Note that for beta, and for following variables, we will aggregate them in our summaries (instead of reporting them individually for each of our Nasdaq\_100 stocks) since it appears that we are interested in their aggregate correlation in the assignment.*

*Furthermore, since each factor should be independent of the stock once isolated, we can presume that this is the justified approach.*

**Summary Statistics for [ beta ] variable**

N: 21481

mean: 1.2417

standard deviation: 0.7829

median: 1.1043

minimum: -2.2283

1st Percentile: -0.1209

99th Percentile: 3.8351

maximum: 7.3953

**Task 2 – Estimating Idiosyncratic Volatility**

Ang et al. cites the following 3-factor model to model the expected returns for each stock



for security i at time t

That is, for our regression, for each stock and for each month, we run the ff3 regression, using data from both at day (t).

In our initial regression, we obtain for each security i:

* Each factor beta
* Our alpha coefficient

Then using the values from above we calculate

* our epsilon for each time t

Why is this not look-ahead bias?

* Because the epsilons are actually part of the portfolio, and
* An investor would use this data calculated from month to make their decision in what to invest in for month if they are interested in the stock's idiosyncratic risk.

Note that when we run our regression, we change our volatility from daily to monthly, meaning we will need to multiply our epsilons by the square root of the number of days in that month (the number of measurements).

We end up with the following statistics

**Summary Statistics for [ ivol ] variable**

N: 21952

mean: 0.0763

standard deviation: 0.0557

median: 0.0604

minimum: 0.0060

1st Percentile: 0.0189

99th Percentile: 0.2845

maximum: 1.0141

**Task 3 – Estimating momentum**

This approach taken for this task is mostly the same as the previous two, except for one important measure.

Since some periods can have less than 12 observations (10, or 11), we get the geometric mean return and then compound to 12 periods. This way, all our data points correctly showcase a 12-month compound return.

**Summary Statistics for [ mom ] variable**

N: 21565

mean: 0.2610

standard deviation: 0.7422

median: 0.1655

minimum: -0.9723

1st Percentile: -0.6760

99th Percentile: 2.7300

maximum: 26.3729

**Task 4 – Winsorize**

Like in assignment 2, we winsorize at the top and bottom 3 standard deviations for every month.

**Summary Statistics for [ beta ] variable (winsorized)**

N: 21481

mean: 1.2396

standard deviation: 0.7679

median: 1.1043

minimum: -2.0165

1st Percentile: -0.1209

99th Percentile: 3.8008

maximum: 5.8011

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**Summary Statistics for [ ivol ] variable (winsorized)**

N: 21952

mean: 0.0754

standard deviation: 0.0518

median: 0.0604

minimum: 0.0060

1st Percentile: 0.0189

99th Percentile: 0.2669

maximum: 0.5325

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**Summary Statistics for [ mom ] variable (winsorized)**

N: 21565

mean: 0.2436

standard deviation: 0.5649

median: 0.1655

minimum: -0.9723

1st Percentile: -0.6750

99th Percentile: 2.2863

maximum: 10.1792

**Task 5 – Correlation between beta and ivol**

We compare the correlation between our winsorized beta and ivol statistics. We arrive at a correlation coefficient of 0.3606, illustrated by the following graph.

A chart of a number of dots

Description automatically generated

This information suggests a weak positive correlation between a stock’s beta and level of idiosyncratic volatility. If we follow this weak data correlation, we can conclude that the higher a stock’s beta, the higher the stock’s idiosyncratic volatility, the portion of the stock’s risk that cannot be removed through diversification.

In the theory, the CAPM beta of a security is typically a measure of how much idiosyncratic risk it holds compared to its benchmark. This theory is therefore seen in a weak level in the data, varying significantly in our 3-factor model leading to a weak correlation.

**Task 6 – Looking for Correlations**

We run a series of correlation analysis between month t+1 stock return and our winsorized factors to see if there are any linear associations.

*For the three variables brought in from Assignment 2, I decided to compare them to month t returns instead, since we already applied a 3-month lag to their base components (from financial reports), meaning that there won’t be any look-ahead bias as investors will always be looking at financials from the past 3 months to make investment decisions.*

Below are the resultant scatter plots with each of the relationships being investigated.

A chart of stock data

Description automatically generated with medium confidence

A chart of a number of dots

Description automatically generated with medium confidence

A chart of different colored dots

Description automatically generated

A chart with green and yellow dots

Description automatically generated

A chart of different colored dots

Description automatically generated

A graph showing a number of earnings

Description automatically generated with medium confidence

**Correlation Matrix**

**A screen shot of a black and white screen

Description automatically generated**

Our correlation matrix yields the conclusion that expected returns are significantly correlated (p < 0.05) with idiosyncratic volatility, momentum, book-to-market, and earnings-to-price ratios, albeit at rather low correlation coefficients. This mostly matches the findings and learnings from class.

* For idiosyncratic volatility, we have learned that investors are rewarded for taking on more idiosyncratic risk.
* For momentum, we have learned that a momentum portfolio generally performs well.
* For book-to-market, we have learned that value stocks (high book-to-market) tend to outperform growth stocks (low book to market).
* For earnings-to-price, we see that stocks prices tend to swing dramatically to earnings results when they either outperform or underperform expectation.

Betas and market capitalization do not appear to be significant factors in estimating returns using a linear relationship, which makes sense from our theory. First of all, we have shown that the CAPM model fails at predicting returns, and our findings here once again repeat that finding. Next, we should not expect that large-cap companies return any higher returns. In fact, we have learned from class that small-cap companies actually are the ones that return higher expected returns.