Financial Economics 251

Cliff Asness's Quality: Explained and Extended

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1 Introduction

Warren Buffett wrote in a 1989 letter to Berkshire shareholders that "it's far better to buy a wonderful company at a fair price than a fair company at a wonderful price." By that, he means that great companies possess competitive advantages and robust margins, and these strengths translate into market-beating returns over the long run. Buffett's track record speaks for itself, but from an efficient market perspective, it makes little sense that companies with stronger fundamentals should generate higher returns. Asset pricing models assume that investors are compensated with higher returns only by taking higher levels of risk. So it is particularly interesting that when we consider Buffett's history and the history of the stock market in general, "quality" stocks (which are intuitively less risky) earn a considerably higher return than can be explained by the CAPM or the SMB, HML, and momentum factors. This assignment explains one measure of Quality which Asness et. al (2013) derived from the Gordon Growth Model, and it provides an analysis that portfolios organized on Quality generate alpha against the CAPM and Carhart Four Factor Model.

2 Quality Explained

Quality is a measure of the likelihood of a company to generate profits over time. Asness et. al turned to a familiar tool to quantify the Quality of a company: the Gordon Growth Model (GGM). The GGM explains that the current price to book value (P/B) of a company is equal to the dividend it pays divided by the difference between the company's discount and growth rates. In mathematical terms, this relationship can be written as:

$$\frac{\text{dividend / book}}{\text{discount rate - growth}} = \frac{\text{profit / assets x payout / profits}}{\text{discount rate - growth}} = \frac{\text{profitability x payout ratio}}{\text{discount rate - growth}}$$

This third term is particularly useful, as it decomposes Quality into three variables which investors can easily calculated: Profitability (adjusted for accrual / payout ratio), Safety (companies with higher discount rates are less safe), and Growth. All else held equal, companies that are more profitable, safer, and higher-growth should be of higher quality. Asness et. al condense many measures of those three variables into three z-scores, before then finding a z-score from the sum of those z-scores. They call this final z-score Quality.

Cliff Asness's hedge fund, AQR Capital, publishes monthly returns of decile portfolios with increasing Quality. I use those portfolios to try and replicate the findings in Asness et. al that Quality finds α against the CAPM and Carhart Four Factor Model. I first regress the Quality portfolio returns (less the risk free rate) from Sept. 1957 to Dec. 2016 against the appropriate factors (MKT-RF for the CAPM and MKT-RF, SMB, HML, and UMD/Momentum for the Carhart Four Factor Model) to find each portfolio's factor loadings and α against the respective asset pricing model. I then calculate the Gibbons-Ross-Shanken F-Statistic and corresponding p-value for each pricing model, which tests the hypothesis that the α's are jointly 0 – or in other words, that the asset pricing model can correctly price Quality portfolios.

The factor loadings and test statistics for the Quality portfolios against the CAPM:

Portfolio	α	β_{MKT-RF}	Portfolio	α	β_{MKT-RF}
1	-0.41	1.34	6	0.05	1.00
2	-0.15	1.21	7	0.08	1.00
3	-0.10	1.08	8	0.00	0.98
4	-0.04	1.05	9	0.15	0.95
5	-0.05	0.97	10	0.15	0.92

GRS F-Statistic: 3.320, p-value: 3.2×10^{-4}

The factor loadings and test statistics for Quality portfolios against the Carhart Four Factor Model:

Portfolio	α	β_{MKT-RF}	β_{SMB}	β_{HML}	β_{UMD}
1	-0.44	1.24	0.59	0.10	-0.10
2	-0.23	1.19	0.30	0.25	-0.05
3	-0.14	1.07	0.18	0.22	-0.07
4	-0.09	1.07	0.05	0.23	-0.04
5	-0.09	1.014	-0.07	0.24	-0.04
6	0.01	1.03	-0.02	0.14	0.01
7	0.02	1.01	0.01	0.13	0.03
8	-0.02	1.00	-0.03	0.06	0.01
9	0.20	0.95	-0.07	-0.08	-0.01
10	0.25	0.89	-0.12	-0.34	0.04

GRS F-Statistic: 5.834, p-value: 1.8×10^{-8}

The above tables are very similar to the resutls presented in Asness et. al. They have interesting interpretations. First, neither the CAPM nor the Carhart Four-Factor Model accurately price the Quality portfolios, as both tests produce an F-statistic corresponding to a p-value significantly smaller than 0.05. This implies that a strategy with Quality could potentially provide a Sharpe Ratio higher than any possible on the efficient frontier spanned by the factors in the Carhart Four Factor Model. Interestingly, while both models fail, the more primitive CAPM does a better job of pricing Quality portfolios than the Carhart Four Factor Model, as evidenced by the lower p-value. Second, higher quality (higher numbered) portfolios generate positive α while lower quality (lower numbered) portfolios generate negative α. This result behooves the creation of a portfolio comprised by shorting stocks with low Quality and going long stocks with high Quality. Asness et. al call this factor Quality Minus Junk, or QMJ – in line with Fama-French factor nomenclature. Third, Quality shares clear relationships with some other factor loadings. Higher Quality generally corresponds to lower β against the market, SMB, and HML. This makes Quality particularly attractive, as it performs well when the other factors perform poorly. The negative relationship with HML is particularly interesting, as the GGM theoretically predicts P/B, the same measure used in HML. However, it makes sense when you consider what the two factors are: Quality refers to picking robust companies regardless of price while HML refers to picking companies with great prices regardless of how robust they are. Finally, Quality is relatively uncorrelated with momentum.

3 Quality Extended

As an extension of Asness et. al's work, I conducted the above analysis on AQR's Quality portfolios for the ten years from Sept. 2011 to Sept. 2021. This test should conclude whether or not the above results hold for current times (see: Conclusion). I have listed the test statistics below. I do not include factor loadings because they are very similar to the results above. They can be found in the code supplement.

The test statistics for Quality portfolios against the CAPM:

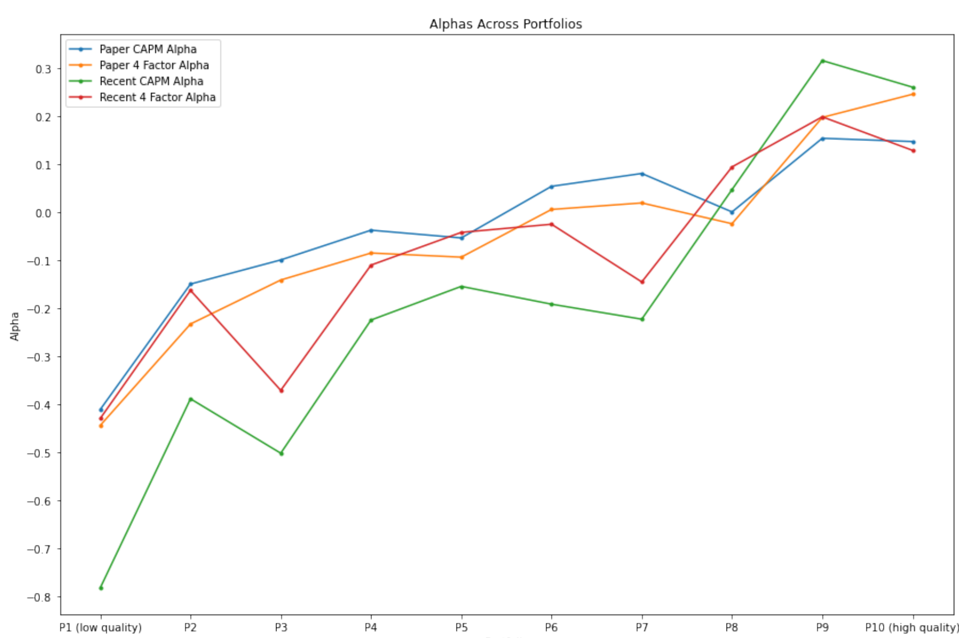
GRS F-Statistic: 1.119, p-value: 0.03

The test statistics for Quality portfolios against the Carhart Four Factor Model:

GRS F-Statistic: 1.843, p-value: 0.06

This time, the Carhart Four Factor Model performs better than the CAPM. We reject the null hypothesis that α's are jointly different from 0 at a significance level of 0.05 for the CAPM while we do not for the Carhard Four Factor Model. However, this does not mean that the Quality effect has disappeared. More likely, there was not enough data to find a significant result; if we had used daily returns or considered more portfolios, we might have found a significant result.

As a final display of my results, I have included a graph of the α's for all ten Quality portfolios across all four tests below. It shows what we expect, namely that α's increase with Quality.



4 Conclusion

In summary, this paper introduced the concept of Quality investing as defined by Asness et. al, found that Quality produces α against the CAPM and Carhart Four Factor Model, and extended that result to modern time periods using the augmented dataset published by AQR. Touching back on the introduction, it is difficult to explain why Quality produces an excess return. Every time a strategy produces a superior return, someone must be willing to take on the opposite side of that bet and accept a lower return. There are two schools of thought on the "opposite-side investor." From a Fama-French efficient market perspective, the opposite side investor accepts a lower return in return for lower risk. From an Lakonishok-Shleifer-Vishny (LSV) behavioral perspective, the opposite side investor systematically underprices stocks due to an asymmetric return curve (they seek very high returns) or irrational exuberance. Neither story makes much sense with Quality; it is hard to argue that Quality companies encompass more risk or investors systematically underprice them. This naturally leads to the question: is Quality, like the January Effect, an anomoly that will be traded out of existence? My analysis (see: Quality Extended) concludes that Quality persists today. All that is left is to determine why.

References

Data from AQR. Quality Minus Junk: 10 Quality-Sorted Portfolios, Monthly.

Data from AQR. Quality Minus Junk: Factors, Monthly.

Asness, Cliff, Andrea Frazzini, and Lasse H. Pedersen (2017). Quality Minus Junk. AQR.

Code Supplement

Here is a link to the GitHub containing the Jupyter Notebook used in this project along with the Excel datasets and paper referenced above. This is the URL:

`https://github.com/anup-bottu/econ251_writing_assignment.`

I have included a PDF of the Jupyter Notebook on the following pages.

Econ 251 Writing Asssignment Supplement

Anup Bottu

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as sm
import scipy.stats as stats

import warnings
warnings.filterwarnings("ignore")
```

```
# import factors
xls = pd.ExcelFile("Quality Minus Junk Factors Monthly.xlsx")
mkt_series = 100*pd.read_excel(xls, "MKT", skiprows = 18, index_col = 0).loc[:, "USA"]
smb_series = 100*pd.read_excel(xls, "SMB", skiprows = 18, index_col = 0).loc[:, "USA"]
rf_series = 100*pd.read_excel(xls, "RF", skiprows = 18, index_col = 0).loc[:, "Risk Free R
hml_series = 100*pd.read_excel(xls, "HML FF", skiprows = 18, index_col = 0).loc[:, "USA"]
umd_series = 100*pd.read_excel(xls, "UMD", skiprows = 18, index_col = 0).loc[:, "USA"]

factors_df = pd.DataFrame({"MKT-RF": mkt_series-rf_series, "SMB": smb_series, "HML": hml_s

# import quality portfolios
xls = pd.ExcelFile("Quality Minus Junk 10 QualitySorted Portfolios Monthly.xlsx")
quality_portfolios_df = 100*pd.read_excel(xls, "10 Portfolios Formed on Quality", skiprows
```

```
# function that performs time series regression

def perform_time_series_regression(factor_names, index):

    factors = factors_df.loc[:, factor_names]
    error_terms_df = pd.DataFrame(columns = quality_portfolios_df.columns)
    factor_loadings_df = pd.DataFrame(index = quality_portfolios_df.columns, \
        columns = ["Alpha"] + factor_names)

    # Time Series Regression
    for portfolio in quality_portfolios_df.columns:
        Y = quality_portfolios_df.loc[index, portfolio] - rf_series.loc[index]
        X = sm.add_constant(factors.loc[index, :])
        regression_result = sm.OLS(Y, X, missing = "drop").fit()
        error_terms_df[portfolio] = regression_result.resid
        factor_loadings_df.loc[portfolio, :] = list(regression_result.params)

    # Calculate GRS F-Statistic and p-value
    omega = mkt_series.var()
    a = factor_loadings_df.loc[:, "Alpha"].to_numpy()
    mu = mkt_series.mean()
    sigma = error_terms_df.cov().to_numpy()

    W = a.dot(np.linalg.inv(sigma)).dot(a) / (1 + mu * omega**(-1) * mu)

    T = len(index)
```

```
    N = len(quality_portfolios_df.T)
    L = len(factors.T)
    W_normalized = W * (T/N) * (T-N-L) / (T-L-1)

    print("Alphas and Factor Loadings:")
    display(factor_loadings_df)
    print(f'F-Statistic = {W_normalized}')
    print(f'p-value = {1 - stats.f.cdf((W_normalized), N, T-N-L)}')

    return factor_loadings_df.iloc[:, 0]
```

```
# storing alphas for final figure

alphas_df = pd.DataFrame(index = quality_portfolios_df.columns, \
    columns = ["Paper CAPM Alpha", "Paper 4 Factor Alpha", \
        "Recent CAPM Alpha", "Recent 4 Factor Alpha"])
```

Part I: Recreating Paper Results (1957-2016)

```
paper_index_end = quality_portfolios_df.index.get_loc("2016-12-31")
paper_index = quality_portfolios_df.iloc[: paper_index_end, :].index
index = paper_index.intersection(factors_df.index)
```

a) Testing Quality Portfolios Against the CAPM

```
factor_names = ["MKT-RF"]
alphas_df.loc[:, "Paper CAPM Alpha"] = perform_time_series_regression(factor_names, index)
```

```
Alphas and Factor Loadings:
```

	Alpha	MKT-RF
P1 (low quality)	-0.410589	1.341999
P2	-0.149642	1.211163
P3	-0.099504	1.076454
P4	-0.037613	1.047318
P5	-0.053721	0.967851
P6	0.053595	0.999716
P7	0.08033	0.990277
P8	0.000342	0.979799
P9	0.153521	0.952708
P10 (high quality)	0.146755	0.918196

```
F-Statistic = 3.3199896602686385
p-value = 0.00031514321596504136
```

b) Testing Quality Portfolios Against the Carhart Four Factor Model

```
factor_names = ["MKT-RF", "SMB", "HML", "UMD"]
alphas_df.loc[:, "Paper 4 Factor Alpha"] = perform_time_series_regression(factor_names, ir
```

```
Alphas and Factor Loadings:
```

	Alpha	MKT-RF	SMB	HML	UMD
P1 (low quality)	-0.443717	1.238949	0.589928	0.1026	-0.104855
P2	-0.23276	1.192931	0.295913	0.250473	-0.050216
P3	-0.141279	1.070805	0.181667	0.224971	-0.074979
P4	-0.08511	1.070812	0.045133	0.227299	-0.044032
P5	-0.093681	1.014299	-0.07024	0.236371	-0.037878
P6	0.005517	1.028321	-0.024476	0.138381	0.008492
P7	0.019022	1.014085	0.006753	0.128555	0.025329
P8	-0.024154	0.996193	-0.025295	0.062845	0.009993
P9	0.19693	0.949774	-0.067705	-0.080217	-0.011575
P10 (high quality)	0.245146	0.888102	-0.118373	-0.339853	0.037571

```
F-Statistic = 5.834649246744047
p-value = 1.7598182910916194e-08
```

Part II: Extending Paper Results (2011-2021)

```
paper_index_start = quality_portfolios_df.index.get_loc("2011-09-30")
paper_index = quality_portfolios_df.iloc[paper_index_start: , :].index
index = paper_index.intersection(factors_df.index)
```

a) Testing Quality Portfolios Against the CAPM

```
factor_names = ["MKT-RF"]
alphas_df.loc[:, "Recent CAPM Alpha"] = perform_time_series_regression(factor_names, index
```

```
Alphas and Factor Loadings:
```

	Alpha	MKT-RF
P1 (low quality)	-0.781595	1.445675
P2	-0.388346	1.302777
P3	-0.501506	1.163944
P4	-0.224508	1.082327
P5	-0.154477	0.997975
P6	-0.191525	1.079568
P7	-0.222719	1.012887
P8	0.046912	1.022303
P9	0.315203	0.922847
P10 (high quality)	0.259821	0.881338

```
F-Statistic = 2.1194875360432115
p-value = 0.028591370915635128
```

b) Testing Quality Portfolios Against the Carhart Four Factor Model

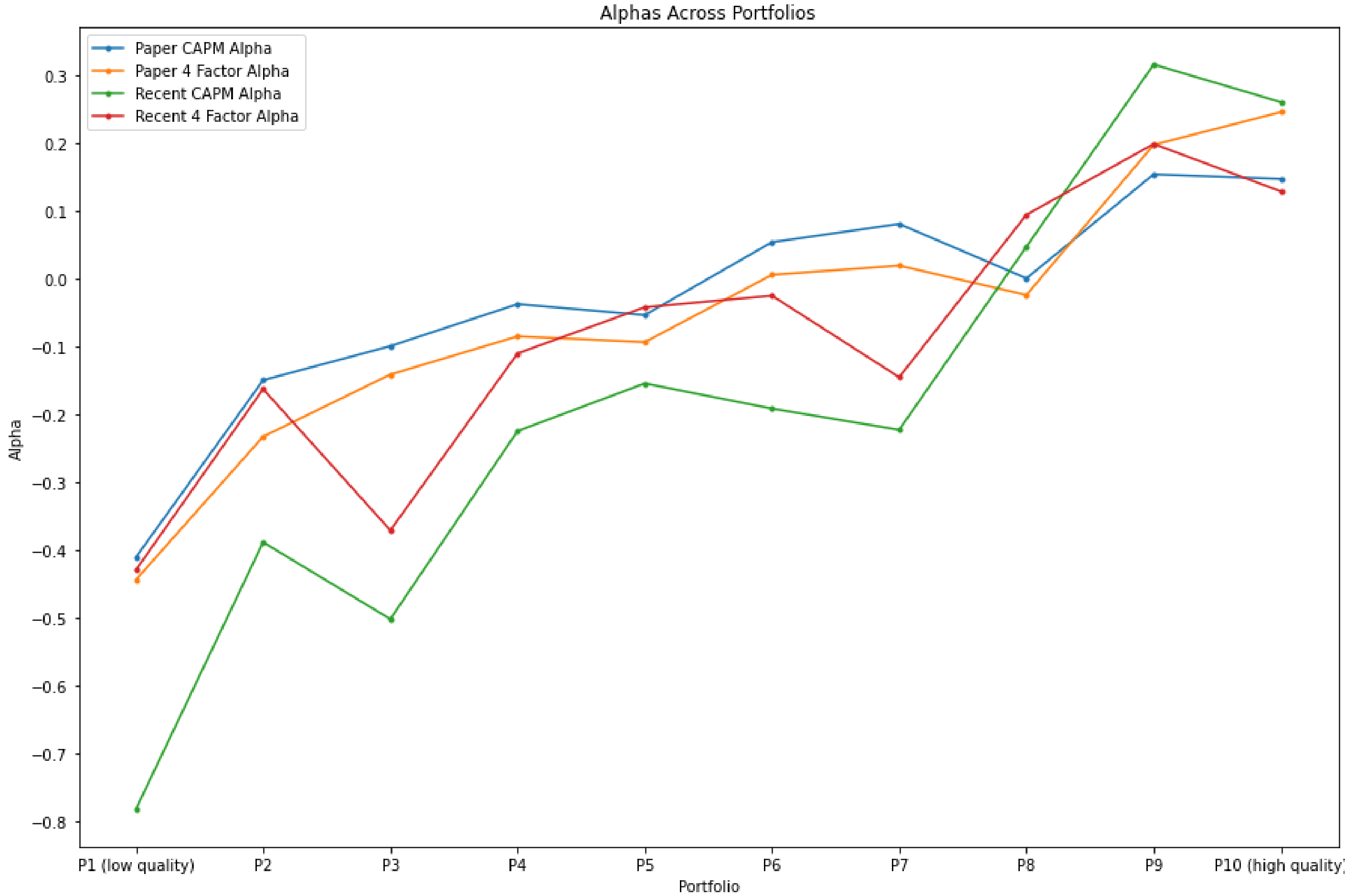
```
factor_names = ["MKT-RF", "SMB", "HML", "UMD"]
alphas_df.loc[:, "Recent 4 Factor Alpha"] = perform_time_series_regression(factor_names, i
```

```
Alphas and Factor Loadings:
```

	Alpha	MKT-RF	SMB	HML	UMD
P1 (low quality)	-0.429259	1.133422	1.134669	-0.053456	-0.084346
P2	-0.162739	1.122361	0.623549	0.029621	-0.051337
P3	-0.370756	1.068161	0.301353	0.038186	-0.038503
P4	-0.110232	1.041178	0.211774	0.269331	0.09755
P5	-0.042202	0.977792	-0.021164	0.26231	0.009845
P6	-0.02524	1.012231	0.111166	0.235261	-0.030432
P7	-0.145269	0.988021	0.031569	0.138689	-0.003089
P8	0.093963	1.002055	-0.029919	0.024788	-0.057844
P9	0.198181	0.988289	-0.1262	-0.080073	0.05816
P10 (high quality)	0.128384	0.946998	-0.234363	-0.190567	-0.032901

```
F-Statistic = 1.843218556723222
p-value = 0.06157629066573567
```

```
ax = alphas_df.plot(style='.-', figsize=(15,10), title = "Alphas Across Portfolios", ylabe
ax.locator_params("y", nbins = 15);
ax.set_xticks(range(0,10));
ax.set_xticklabels(quality_portfolios_df.columns);
```


Alphas Across Portfolios
Paper CAPM Alpha
Paper 4 Factor Alpha
Recent CAPM Alpha
Recent 4 Factor Alpha
Alpha
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.6
−0.7
−0.8
P1 (low quality)
P2
P3
P4
P5
P6
P7
P8
P9
P10 (high quality)
Portfolio