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Investigating Quality Minus Junk

The role of shorting, market beta, firm size and value in the quality minus junk anomaly

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Abstract

The quality factor of Asness, Frazzini and Pedersen (2013) combines several quality dimensions, identified in previous literature, into one strategy which presents an asset pricing puzzle of quality being positively correlated with prices yet very weakly describing them, and at the same time quality minus junk being significantly profitable. I document similar results by following their construction methodology and observe QMJ profits to be dominated by the short side. I find that quality and value are hedges and higher returns can be achieved by combining the two strategies. I also find evidence of a robust size effect and the beta anomaly by sorting quality within size and market beta portfolios. Lastly, I observe that a managed volatility portfolio, which limits risk exposure when volatility is high, produces a significant alpha for quality.

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1. Introduction

The literature on finance has been trying to explain asset returns for more than half a century, with a multitude of new explanatory factors and strategies materializing regularly. However, none of these factors, or combination of factors, has managed to fully explain the movement of asset returns. These factors are, on the other hand, immensely useful in decoding at least a section of return variation and in the process increasing understanding of the explanatory variables themselves, if not returns. Quality, as a factor and strategy, is relatively newer and presents a puzzle for asset pricing. Different dimensions of quality have been investigated in isolation for a long time, such as Ohlson (1980) and Altman (1968) find that high credit risk is linked to lower firm performance, Mohanram (2005) shows that high growth firms have higher returns, the beta anomaly is documented by Black, Jensen, and Scholes (1972), George and Hwang (2010) find that firms which are highly leveraged have lower alphas, and Novy-Marx (2013) shows the low profitability stocks underperform high profitability stocks. Asness, Frazzini and Pedersen (2013) have combined several of these quality characteristics, namely profitability, growth, safety and payout, into one quality factor. I explore the quality factor, first by following their methodology and then investigating its behavior within value, size, and beta and after managing volatility, by varying risk exposure with volatility.

For the construction of quality and obtaining results, I follow the 2013 draft of 'Quality Minus Junk' by Asness, Frazzini and Pedersen, since it retains payout as a quality component. My results are largely in agreement with those of the original paper. To test the effect of quality on prices, monthly cross sectional regressions of market to book are run on quality scores and the time series average reflects a positive and significant effect of increasing quality on prices. However, the explanatory power is quite low at a 12% R squared combined with the puzzle of obtaining significantly high excess returns and alphas from quality stocks and the quality minus junk strategy. This motivates several possible explanations including thinking of quality as a behavioral anomaly where the market underprices quality, quality representing some form of risk which is not captured within the negative market beta of the safety component, and the construction of quality not reflecting characteristics that command higher prices in the market. The second explanation is challenged, as a result of showing that QMJ (quality minus junk) is negatively related to the market and the quality minus junk strategy involves longing low beta and shorting high beta stocks. Also, QMJ is seen to be negatively related to size and value. I find QMJ to be significantly positively related to momentum, unlike the insignificant relationship in the paper. Another avenue where my results deviate slightly from the original is in the magnitude of excess returns and alphas, as I obtain higher observations. This may be due to the inadvertent smaller sample size as a result of my methodology, details of which are provided in Section 2, Appendix A1 and A2.

Additionally, I investigate the contribution of long and short side profits to overall QMJ profits and find that they are dominated by the short side. This points toward a possible limited explanation of high QMJ returns, as shorting junk may be inherently risky but mispriced. After exploring the performance of Asness, Frazzini and Pedersen's quality, I move on to investigating its relationship with value, size and beta in a more explicit fashion. To do this, I utilize double sorts by sorting quality within the other factor portfolios. I confirm the earlier negative relationship of quality and value, observed by Asness, Frazzini and Pedersen (2013), by showing the decreasing excess return and alpha of QMJ as value increases. However, the long side, or the returns from quality stocks, increase monotonically as value increases and I find that the highest returns may be obtained by longing value quality stocks and shorting growth junk stocks.

Quality within size behaves similarly to value, and QMJ return and alpha decrease as size increases. Israel and Moskowitz (2013) find that more than 100% of value returns and the majority of alphas come from the long side. I find that the majority of QMJ excess returns and, on average, half of QMJ alphas come from the long side. I observe that small quality stocks offer higher returns than big quality stocks and this offers insight into the composition of quality. Excess returns observed from junk improve as size increases. Bigger firms are generally thought to be higher quality firms, in terms of profitability, safety etc., than smaller firms which pose a larger risk. However, quality does not necessarily move in that fashion as it can be seen that small firms also offer significant high excess return and alpha of longing quality. Intuitively, if the quality factor was linked with firm size, with bigger firms being higher quality firms, the QMJ factor would not provide to be profitable. Therefore, quality stocks also include smaller firms and the highest excess returns may be obtained by longing small quality stocks and shorting small junk stocks.

I observe the highest alpha from low beta quality stocks and the lowest alpha from high beta junk stocks. As beta increases, the percentage contribution to alphas from quality stocks decrease and contribution from junk increases monotonically. This is also in line with the negative relationship of QMJ with the market excess return observed by Asness, Frazzini and Pedersen (2013). Finally, managing volatility by scaling monthly factor returns with the inverse of realized (past month) variance in stock return, such that the managed factor return increases if volatility decreases and vice versa, may improve returns of various strategies, the strongest of which is momentum as observed by Moreira and Muir (2017). I show that QMJ returns improve slightly by managing volatility but the impact is not as strong as momentum and the difference between Sharpe ratios is found to be insignificant for all factors, including QMJ, except momentum.

Summarizing the main findings of this study, my results show that QMJ profits largely come from shorting junk. The quality and value strategies may be hedges for each other and higher premiums are shown to be obtained by combining value and quality. Even though QMJ is negatively correlated with SMB (size), and therefore thought of as long big and short small stocks, my results show that higher premiums are obtained by longing small quality and shorting small junk stocks. I also show that controlling for beta decreases quality premiums and profits. The beta anomaly is documented by finding that abnormal returns may be improved by longing low beta quality stocks and shorting high beta junk stocks. Lastly, I find that managing volatility marginally improves the performance of the quality strategy.

The rest of this document is organized as follows. Section 2 discusses additional literature which relates to the findings of this thesis. Section 3 illustrates the sources and assembly procedures of data, specifically the construction of quality, QMJ and the managed volatility factors. Next, Section 4 addresses analysis methodology and reports results along with their implications. This section first reports results of replicating Asness, Frazzini and Pedersen (2013) and then moves on to looking at quality in relation to other factors and after managing volatility. Finally, Section 5 concludes this study.

2. Literature Review

In addition to the papers already mentioned, the subject matter of this thesis is linked to a broad asset pricing literature. Banz (1981) finds that big firms command higher prices, and hence lower returns. This is dubbed the size effect and the phenomenon of smaller firms outperforming bigger firms, in terms of excess returns, is documented repeatedly, for instance by Fama and French (1992). Asness, Frazzini and Pedersen (2013) find that big firms continue to command higher prices even after controlling for quality, so the size effect remains robust. My findings agree with this. I also find that small quality firms tend to outperform big quality firms, and hence the size effect remains present even alongside QMJ returns being negatively correlated with SMB.

The role of longing and shorting is investigated among the SMB (size), HML (value) and UMD (momentum) strategies by Israel and Moskowitz (2013). They find that long positions make up most of SMB profits, more than half of HML profits and half of momentum profits. I, on the other hand, find QMJ profits to be made up mostly of short positions. This is a departure from the behavior of the preceding three strategies.

Value stocks have been documented, time and again, to outperform growth stocks by Stattman (1980), Rosenberg, Reid and Lanstein (1985), DeBondt and Thaler (1985), Fama and French (1992), Lakonishok, Shleifer and Vishny (1994) etc. Israel and Moskowitz (2013) test the performance of the value strategy within size and find that the value premium decreases with firm size and shorting becomes less important for value as firm size increases. My results conform to these findings. Furthermore, I test QMJ within size and find quality to behave similarly to value, with the quality premium decreasing as firm size increases. Momentum, however, as explored by Israel and Moskowitz (2013), did not show a clear relationship with size. I also find that the role of shorting either remains equally important or increases for QMJ as firm size increases, which is opposing the behavior of value within size and similar to the behavior of momentum within size as found by Israel and Moskowitz (2013).

Frankel and Lee (1998) show the usefulness of analyst based valuation models and Piotroski (2000) emphasizes the effectiveness of historical financial statement information in improving value investing. I also find that the use of accounting information, in the form of QMJ, can improve returns from the value strategy and the best returns are obtained by longing value quality stocks and shorting growth junk stocks. Also, Novy-Marx (2013) states that value and quality may be hedges for each other and my findings also show high value stocks to exhibit lower QMJ premiums while growth stocks show higher QMJ returns.

The debate regarding risk vs. mispricing has continued in asset pricing, with support for both sides strengthening as market anomalies are documented to remain robust across different assets, time and stock markets, by a vast amount of literature such as Chan, Hamao and Lakonishok (1991), Hawawini and Keim (1995), Fama and French (1998 and 2012) and more. A similar explanation challenge faces QMJ with my results conforming to Asness, Frazzini and Pedersen (2013) who find that although quality does command higher prices to an extent, it does not explain much variation in prices and it also exhibits higher excess returns. Furthermore, QMJ returns are seen to be negatively correlated with the market, pointing toward a possibility that quality stocks are low beta and hence low risk. Overall, QMJ remains a puzzle with respect to risk and mispricing explanations.

I, on the other hand, find quality’s behavior within low and high beta portfolios to be interesting with the quality premium increasing as beta increases. However, I also find that shorting junk becomes more important for QMJ as beta increases and the highest abnormal returns can be obtained by longing low beta quality stocks and shorting high beta junk stocks. This result conforms to the beta anomaly found by Black, Jensen and Scholes (1972). Moreover, I find QMJ abnormal returns, in the form of three and four factor alphas, to remain robust within separate beta portfolios and this contradicts Ruomeng Liu (2018, working paper) who finds that abnormal returns associated with other anomalies diminish after controlling for beta.

Additional details regarding this result and all preceding referenced results can be found in a forthcoming section, labelled empirical analysis.

3. Data Description

This section addresses data sources, as well as the process for construction of quality minus junk (QMJ) and volatility managed factors.

I use monthly stock return data from CRSP and annual stock fundamentals from the CRSP/Compustat Merged database. The long sample consists of 23,259 U.S. common stocks[1] and runs from June 1951 to December 2012. However, results begin from June 1956, since five years of data are required for some quality characteristics. Missing return observations are replaced with delisting returns, wherever available. The size (SMB), value (HML) and momentum (UMD) factor returns are obtained from the Kenneth R. French data library and also run from June 1956 to December 2012. I obtain both daily and monthly return data for these factors. Daily and monthly QMJ factor returns are obtained, for constructing the volatility managed factor, from the AQR Capital Management data library.

Following the method of Asness, Frazzini and Pedersen (2013), I construct the quality factor as a combination of profitability, growth, safety and payout. Each of the four quality components is calculated by taking an average of a set of individual measure z-scores. The z-scores are computed as

$$Z(x) = R(x) - \mu(R) / \sigma(R)$$

where $R(x)$, $\mu(R)$ and $\sigma(R)$ are the rank of each measure, mean of the ranks and standard deviation of the ranks, respectively. The rank, mean and standard deviation are all cross sectional. The composition of each quality component is illustrated below and details regarding the calculation of each component's measures can be found in Appendix A1.

$$\text{Profitability} = (zGPOA + zROE + zROA + zCFOA + zGMAR + zACC) / 6$$

The measures contained within the profitability component are gross profit over assets, return on equity, return over assets, cash flow over assets, gross margin and low accruals.

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[1] Common stocks are denoted by a share code of 10 or 11 in the CRSP data file and a stock ownership code of 0 in Compustat.

$$\text{Growth} = (z\,\Delta GPOA + z\,\Delta ROE + z\,\Delta ROA + z\,\Delta CFOA + z\,\Delta GMAR + z\,\Delta ACC) / 6$$

The growth measures are the five year growth in all profitability measures.

$$\text{Safety} = (zBAB + zIVOL + zLEV + zO + zAltZ + zEVOL) / 6$$

The safety measures are low beta, low idiosyncratic volatility, low leverage, low bankruptcy risk in the form of Ohlson's O and Altman's Z scores, and low earnings volatility. BAB, betting against beta, is minus market beta and is calculated using the methodology of Frazzini and Pedersen (2013). Excess returns are calculated by deducting the U.S. Treasury bill rate from the value weighted market returns and stock returns. I estimate market beta by first dividing rolling one year standard deviation of excess stock return by rolling one year standard deviation of excess market return, and then multiplying the result with the rolling five year correlation of stock and market. I use monthly data, as opposed to the daily data used in the original paper. IVOL is taken as minus a stock's idiosyncratic volatility and computed by taking rolling one year standard deviation of beta adjusted excess stock return. Again, I use monthly return data, instead of daily, for ease of handling. EVOL is calculated as the standard deviation of annual ROE over the past five years, conditional on five years of non-missing data.

$$\text{Payout} = (zEISS + zDISS + zNPOP) / 3$$

The measures contained within the payout component are net equity issuance, net debt issuance, and total net payout over profits.

$$\text{Quality} = (\text{Profitability} + \text{Growth} + \text{Safety} + \text{Payout}) / 4$$

Finally, the quality score is calculated by taking the average of the four components. In case data for a particular measure is missing, the component score is calculated by averaging the rest of the variables. Similarly for the quality score, the rest of the components are averaged in case of observations where data for a particular component is missing.

Table 1 reports some summary statistics. The number of stocks remaining within quality and its components, after all data manipulations, is reported as N. Also, the mean, standard deviation, minimum and maximum of the quality and component scores can be observed.

Table 1 – Descriptive Statistics

This table reports the number of U.S. common stocks remaining within quality and each quality component after all data manipulations, in the sample period June 1956 to December 2012. The mean, standard deviation, minimum and maximum of the quality scores and each component's scores is also reported.

	N	Mean	SD	Min	Max
Profitability	9,291	0.0632	0.574	-1.73	1.68
Growth	7,547	0.0125	0.662	-1.73	1.73
Safety	9,275	0.0159	0.460	-1.66	1.58
Payout	9,261	0.0189	0.654	-2.12	2.13
Quality	9,291	0.0242	0.395	-1.47	1.45

Quality sorted portfolios are formed by assigning stocks to ten portfolios each month, based on their quality score. They are value weighted and rebalanced every month to maintain their value weights. The portfolio breakpoints are determined using NYSE stocks. The construction of QMJ portfolios follows the methodology of Fama and French (1992, 1993 and 1996). The profitability, growth, safety and payout portfolios are constructed in the same manner as the QMJ portfolios. First, the dataset is split into half based on market capitalization, or size, each month using NYSE breakpoints and ten quality sorted portfolios are formed within the universe of small and big stocks. Quality portfolios one, two and three within the small universe are denoted small junk, and portfolios eight, nine and ten are small quality. Similarly, I obtain big junk and big quality portfolios. The QMJ return is the return from QMJ in both big and small stocks, as illustrated below.

$$\text{QMJ} = (\text{Big quality} - \text{Big junk})/2 \quad + \quad (\text{Small quality} - \text{Small junk})/2$$

Although I follow the data construction of Asness, Frazzini and Pedersen (2013) as closely as possible, Appendix A2 provides all possible deviations from it, where either the method was altered for simplicity or my comprehension of construction could have potentially diverged from the original.

I construct the volatility managed factors using the methodology of Moreira and Muir (2017). My sample period for the market excess return, SMB, HML and UMD excess returns (obtained from the Kenneth R. French data library) runs from January 1927 to December 2015 while the QMJ excess return sample (obtained from the AQR Capital Management data library) runs from August 1957 to December 2015.The Fama and French factor returns and QMJ are scaled by the inverse of their realized variance in the past month, so that if the variance increases, the risk exposure of the managed factor decreases and vice versa. The monthly variance is calculated using daily factor returns. Given below is the expression used for computing volatility managed returns for each factor.

Managed factor return = (C / Squared realized variance in the past month)*Factor return

C is a constant which ensures that the standard deviations of the managed and original factor returns are equal. [2]

Having discussed the data construction methodology, the next section explores results from replicated tables and analyses the behavior of QMJ with respect to other factors and in the context of managed volatility.

[2] I calculate C, for each factor, using Excel Solver.

4. Empirical Analysis

Before moving on to the analysis of the price of quality and abnormal returns associated with it, I first establish that quality scores do in fact rise as required across the quality portfolios and its four components.

Table 2

This table reports the average quality scores across ten quality sorted portfolios in the entire sample period, from June 1956 to December 2012. Each month, stocks are ranked in ascending order based on their quality scores and sorted into ten deciles with the breakpoints based on NYSE stocks. The portfolios are value weighted, and rebalanced every calendar month to maintain their value weights. The time series average of the cross sectional value weighted means of quality scores are reported for each portfolio of quality and its components. The difference between the highest and lowest quality scores is reported along with its t statistic and significance is indicated in bold.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	P10-P1 t-stat
Quality	-0.58	-0.35	-0.22	-0.12	-0.02	0.08	0.18	0.30	0.45	0.74	**1.32**	28.12
Profit	-0.81	-0.47	-0.28	-0.12	0.01	0.16	0.31	0.47	0.68	1.07	**1.88**	38.98
Growth	-1.01	-0.67	-0.46	-0.28	-0.11	0.07	0.24	0.43	0.67	1.11	**2.12**	37.10
Safety	-0.64	-0.40	-0.24	-0.11	0.02	0.13	0.25	0.38	0.54	0.83	**1.47**	36.83
Payout	-1.10	-0.67	-0.42	-0.23	-0.06	0.10	0.27	0.45	0.70	1.08	**2.18**	82.22

Table 2 shows average scores during the sample period, and the difference between the highest and lowest quality portfolios. The averages are found by first taking cross sectional value weighted means throughout the sample, and then determining a time series average, overall. As can be seen, the scores rise monotonically for quality, profitability, growth, safety and payout. This same trend can be seen across the sample, in cross section, and it is thus persistent. Also, I conduct t tests to observe if the difference between the highest and lowest deciles at a certain point in time is statistically significant, or different from 0, and all differences are in fact highly significant. My findings conform to the original paper's results.

Next, I examine how market to book ratio or price to book, moves with quality and its components. This is accomplished by running monthly cross sectional regressions of the standardized z-score of market to book on the quality score of each stock. Table 3 reports the time series average of the resulting regression coefficients. Standard errors are adjusted, using the Newey and West (1987) method, with a lag length of twelve months.

Table 3

This table reports the price of quality for the entire sample (June 1956 to December 2012) of U.S. common stocks. Monthly cross sectional regressions of the standardized z-score of market to book are run on the quality score and component score of each stock. Column (2) of Panel A includes z-score of market equity and one year lagged returns as explanatory variables in the regressions. The time series average of the resulting regression coefficients and R squared is reported. Standard errors are adjusted, using the Newey and West (1987) method, with a lag length of twelve months. T statistics are reported in brackets and significance is indicated in bold.

Panel A: The price of quality

	(1)	(2)
Quality	**0.33**	**0.24**
	(28.51)	(22.89)
Size		**0.33**
		(22.01)
Ret(t-12,t)		**0.04**
		(11.08)
Average R^2	0.12	0.24

Panel B: The price of each quality component

	(1)	(2)	(3)	(4)
Profitability	**0.38**			
	(16.92)			
Growth		**0.38**		
		(22.43)		
Safety			**0.47**	
			(37.09)	
Payout				**-0.10**
				-(9.73)
Average R^2	0.17	0.16	0.22	0.01

As can be seen in column (1) of Panel A, the price of quality is positive and highly significant and it can be concluded that high quality is linked to high prices throughout the sample, in its cross section. The average R squared, however, is a low 12%, which means that quality does not explain a great deal of the variation in prices. This result is in agreement with Asness, Frazzini and Pedersen (2013) and can be interpreted similarly. If the quality score increases by 1 standard deviation, the price increases by 0.33 standard deviations. A time series representation of the cross sectional price of quality can be seen in Figure 1. While varying around 0.3, the price of quality is seen as generally decreasing.

Figure 1

This figure shows the coefficients from cross sectional regressions of standardized z scores of a stock's market to book on its quality. The June 1956 to December 2012 time series of the coefficients of the regression from Panel A, column (1), in Table 3 are shown.

Panel B of Table 3 reports regression results for the separate quality components. The behavior of profitability, growth and safety corresponds to that of quality. However, the average R squared increases in comparison to quality. The individual components explain a greater percentage of the variation in price to book. I observe a much higher price and average R squared of safety compared to the very low values observed by Asness, Frazzini and Pedersen (2013). In fact, my sample shows that safety explains the highest amount of variation in prices, among the quality components, and this departure may be due to inadvertent differences in the construction of safety itself. The price and R squared of payout conform to those in the original paper. Payout is the only factor that has a significant negative price and it only explains 1% of the variation. This implies that low payout firms are more expensive and vice versa and Asness, Frazzini and Pedersen (2013) link this to the issue and repurchase behavior of firms where firms may choose to issue shares when prices are high, and ultimately cause prices to decline while payout rises. It may also be linked to the rise in prices when dividends are announced and then the consequent decline on the ex-dividend date, after being paid out.

Table 3 also reports the results of a multivariate regression where size and past returns are added as explanatory variables alongside quality. Size is measured as a standardized z-score of market equity, and past returns are the standardized z-scores of lagged past year returns. Column (2) of Panel A shows that both size and past returns are positively and significantly associated with current prices, while the coefficient of quality, although slightly weakened, maintains its effect. I find that past returns have a weak association of 0.04 compared to the 0.28 observed by Asness, Frazzini and Pedersen (2013) and this may be due to differences in formation or standardization of the independent variable. These results confirm the size effect, even when controlling for quality, as bigger firms are still associated with higher prices. Also, past returns have an explanatory power for current prices, due to the prices rising while book value needs time to adjust. The average R squared increases, and the inclusion of size and past returns means that 24% of the variation in prices is now explained, however this still leaves the majority of variations unexplained.

Moving on to the risk and return characteristics of quality, I report excess returns, alphas, and betas across the ten quality portfolios in Table 4. Again, I obtain value weighted cross sectional means of excess return and then a time series average, within each decile, which is reported. The Sharpe ratio which is the excess return divided by the standard deviation of the value weighted excess returns in each decile, is reported as well. A time series regression of the value weighted excess stock return on excess market return yields an intercept which is reported as the CAPM alpha and the regression coefficient is reported as beta. Additionally, alphas for the three and four factor models which add SMB, HML and UMD as explanatory variables, along with excess return on the market, are reported. Finally, adjusted R squared and information ratios[3] are reported for the four factor model.

Excess returns and Sharpe ratios increase monotonically, and it can be seen that higher quality stocks offer a higher excess return compared to lower quality stocks. The right most column reports the difference between the highest quality and lowest quality decile and it is significantly different from 0. This presents the old risk vs. mispricing puzzle for asset pricing. Intuitively, holding higher quality stocks should present a lower risk as compared to junk stocks and the excess return may be a result of the market placing a too low price on quality. On the other hand, the construction of quality itself could have resulted in higher quality stocks posing a higher risk. This is explored further by looking at the CAPM alphas and betas across quality. Abnormal returns also increase monotonically as quality increases and the difference between high and low quality is significant.

It is interesting to observe that higher quality stocks have lower betas and vice versa, and this corroborates the mispricing explanation as junk stocks seem to have a higher beta, market exposure and risk while quality stocks score low on the market exposure and consequently , risk scale. Therefore, the construction of quality seems to be sound. I test the behavior of quality within beta sorted portfolios later on to take a more comprehensive look at their relationship. The three factor and four factor alphas for high quality portfolios are higher compared to the CAPM alpha and as Asness, Frazzini and Pedersen (2013) conclude, this is due to the higher quality stocks having a lower exposure to the other factors. I find that the three factor alphas for high quality stocks are the highest, in contrast to the four factor alphas observed by Asness, Frazzini and Pedersen (2013). Adding UMD lowers the alphas observed in the two highest quality deciles slightly while increasing those of portfolio 7 and 8. Also, I observe a much larger spread in excess return and alphas and this may be due to the smaller sample size or differing manipulations in the process of obtaining observations. Generally, my results largely match the trends and conclusions of Asness, Frazzini and Pedersen (2013).

[3] Information ratio is calculated as the four factor alpha divided by the standard deviation of estimated residuals in the four factor time series regression.

Table 4

This table reports return characteristics of quality sorted portfolios for the long sample (June 1956 to December 2012) of U.S. common stocks. Each month, stocks are ranked in ascending order based on their quality scores and sorted into ten deciles with the breakpoints based on NYSE stocks. The portfolios are value weighted, and rebalanced every calendar month to maintain their value weights. The time series average of cross sectional value weighted excess returns within each portfolio is reported and Sharpe ratio is calculated as the excess return divided by the standard deviation of excess return in the portfolio. Alphas are the intercept in a time series regression of the monthly excess return on excess return on the market, SMB, HML and UMD. The information ratio is the four factor alpha divided by the standard deviation of estimated residuals in the time series regression. T statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent. Sharpe ratios and information ratios are annualized by multiplying them with the square root of 12.

	P1 Low	P2	P3	P4	P5	P6	P7	P8	P9	P10 High	H-L
Excess return	**-0.57**	-0.11	0.06	0.25	0.32	**0.47**	**0.57**	**0.57**	**0.66**	**0.89**	**1.46**
	-(2.50)	-(0.56)	(0.30)	(1.29)	(1.78)	(2.63)	(3.16)	(3.2)	(3.79)	(5.16)	(5.10)
CAPM alpha	**-1.14**	**-0.63**	**-0.43**	**-0.26**	**-0.15**	-0.01	0.09	0.10	**0.20**	**0.44**	**1.58**
	-(10.54)	-(7.39)	-(5.40)	-(3.31)	-(2.28)	-(0.02)	(1.43)	(1.55)	(3.15)	(6.18)	(11.14)
3-factor alpha	**-1.28**	**-0.73**	**-0.54**	**-0.33**	**-0.20**	-0.02	0.10	0.13	**0.29**	**0.59**	**1.87**
	-(13.69)	-(9.03)	-(6.96)	-(4.36)	-(2.95)	-(0.21)	(1.51)	(1.98)	(4.67)	(9.29)	(14.56)
4-factor alpha	**-1.16**	**-0.66**	**-0.43**	**-0.24**	**-0.22**	-0.01	0.12	**0.14**	**0.23**	**0.52**	**1.68**
	-(12.34)	-(8.03)	-(5.60)	-(3.08)	-(3.10)	-(0.12)	(1.66)	(2.08)	(3.67)	(8.05)	(13.07)
Beta	1.19	1.08	1.01	1.06	1.00	0.98	0.99	0.98	0.95	0.92	-0.27
Sharpe Ratio	-0.33	-0.08	0.04	0.17	0.24	0.35	0.42	0.42	0.51	0.68	1.02
Information Ratio	-1.29	-1.07	-0.57	-0.33	-0.25	0.10	0.29	0.50	0.61	0.99	2.28
Adjusted R^2	0.85	0.85	0.85	0.86	0.87	0.87	0.86	0.88	0.88	0.87	0.02

The next two tables deal with analyzing the QMJ factor returns, as well as profitability, growth, safety and payout long/short strategy returns. In Table 5, I show correlations between all the factor excess returns. Again, my results are in harmony with Asness, Frazzini and Pedersen (2013) and it can be seen that all factors are positively correlated with each other except growth and payout. Intuitively, it makes sense that growing firms are low payout. I also observe that payout is weakly correlated with the other factors and with quality, while the other factors show higher degrees of correlation.

Table 5

This table reports the correlations between QMJ, profitability, safety, growth and payout strategy monthly excess returns for the long sample (June 1956 to December 2012) of U.S. common stocks. Each calendar month, stocks are assigned to two portfolios based on increasing market equity and breakpoints are established by NYSE. Quality is conditionally sorted within each size portfolio and QMJ and component strategy excess returns are obtained. Portfolios are value weighted and rebalanced every month to maintain their weights.

	QMJ	Profitability	Safety	Growth	Payout
QMJ	1.00				
Profitability	0.90	1.00			
Safety	0.73	0.55	1.00		
Growth	0.72	0.65	0.45	1.00	
Payout	0.34	0.37	0.06	-0.12	1.00

Asness, Frazzini and Pedersen (2013) exclude payout from their construction of quality in their 2017 draft of their paper and the weak correlations, combined with the negative pricing effect observed in Table 3 might have led to this choice. I conduct the same analysis, after excluding payout and did not observe any significant changes in observations[4] and resulting explanations leading to my conclusion that the payout dimension either does not impact quality due to construction or by definition.

The final table I replicate from Asness, Frazzini and Pedersen (2013), describes the excess returns and alphas of QMJ and long/short quality component strategies. The construction of QMJ is outlined in Section 2 and Figure 2 provides a visual representation of increasing cumulative QMJ returns across the sample period.

[4] I can provide these results upon request.

Figure 2

This figure shows cumulative returns of the quality minus junk (QMJ) factor from June 1956 to December 2012. The long sample of U.S. stocks contains all common stocks from the CRSP/Compustat database and the methodology for construction of QMJ follows Asness, Frazzini and Pedersen (2013).

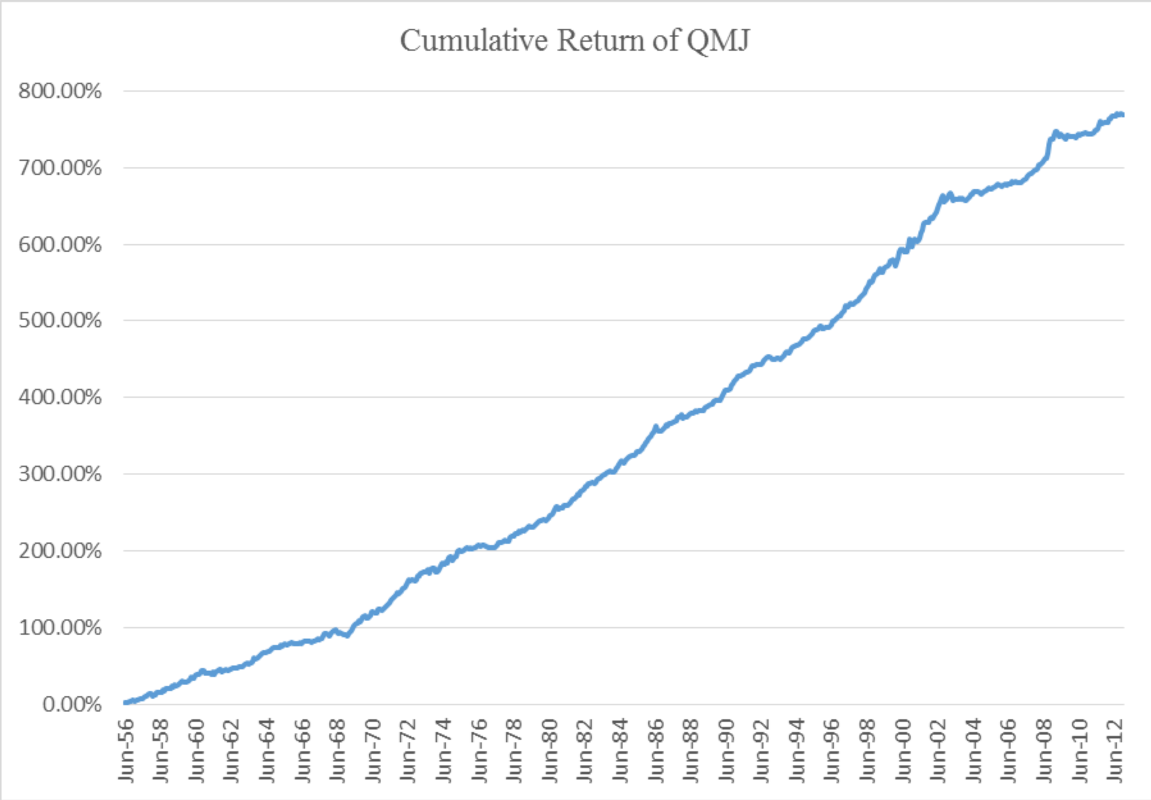


Table 6 details the time series averages of excess returns and the time series regressions of excess returns on the market and the Fama and French factors. I find that QMJ and all component strategies show positive and significant excess returns and alphas. QMJ performs the best overall, followed by profitability, safety, growth and payout. The growth excess return and CAPM alpha, I find are significant as opposed to Asness, Frazzini and Pedersen (2013), who find that they are not significantly different than 0. All other results and conclusions support the original paper. I find that the three and four factor alphas are higher than the CAPM alphas; this was observed in Table 4 as well.

The market factor regression coefficients are negative for all factors, as expected, although it is interesting to note that safety provides the highest negative relationship and confirms that high safety stocks are low beta while low safety stocks are high beta. A similar relationship can be observed with size, quality and all its components strategies show a negative factor loading, except for growth which is insignificant. This also confirms that high quality stocks are long big stocks and short small. A negative value factor coefficient confirms that value, which longs underpriced stocks, is perhaps the opposite of quality which is related to higher priced stocks. Payout is the only component which shows a positive coefficient on value and may again be described by lower priced firms not choosing to issue shares and consequently being low payout while highly priced firms seize the opportunity to issue shares and be high payout. I also find that the quality, profitability, safety and growth strategies have significant and positive factor loadings for momentum and may indicate that QMJ is long high momentum and short low momentum. High quality stocks may also be stocks which offered high past returns. This result is different from the original paper.

Table 6

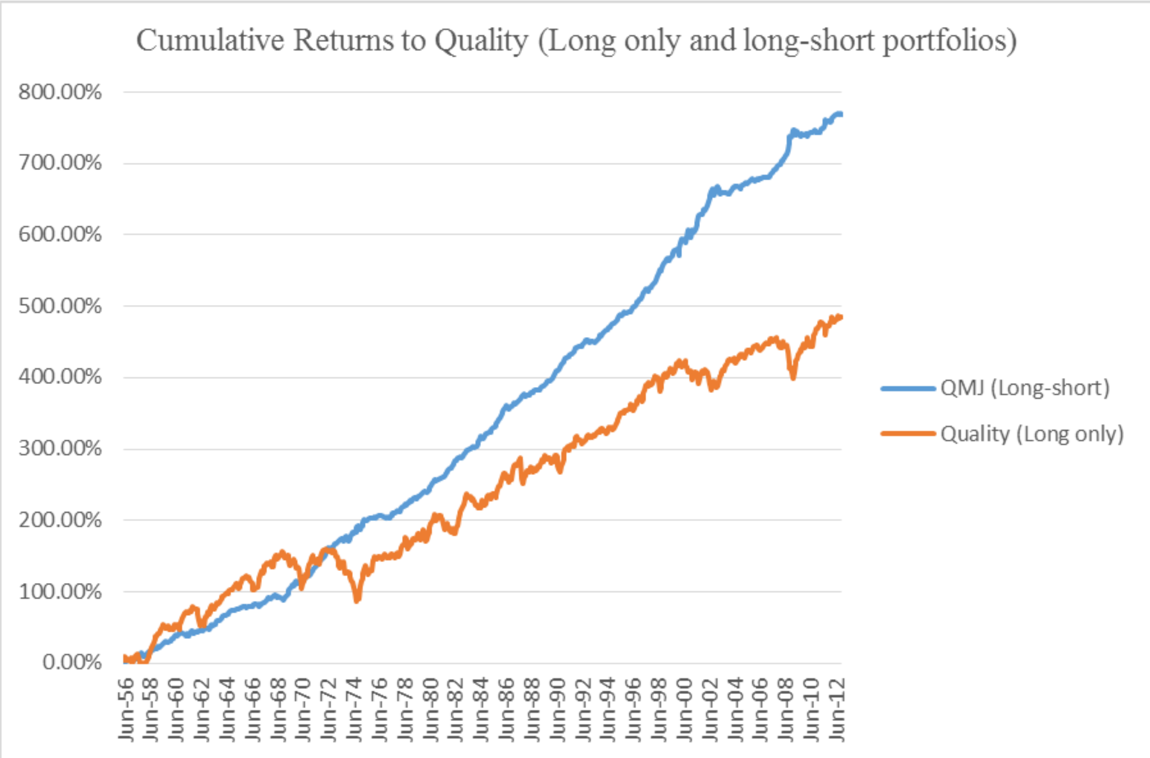
This table reports return characteristics of QMJ and component strategies for the long sample (June 1956 to December 2012) of U.S. common stocks. Each calendar month, stocks are assigned to two portfolios based on increasing market equity and breakpoints are established by NYSE. Quality is conditionally sorted within each size portfolio and QMJ and component strategy excess returns are obtained. Portfolios are value weighted and rebalanced every month to maintain their weights. The time series average of each strategy's excess returns is reported and Sharpe ratio is calculated as the excess return divided by the standard deviation of excess return in the strategy. Alphas are the intercept in a time series regression of the monthly excess return on excess return on the market, SMB, HML and UMD. The information ratio is the four factor alpha divided by the standard deviation of estimated residuals in the time series regression. T statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent. Sharpe ratios and information ratios are annualized by multiplying them with the square root of 12.

	QMJ	Profitability	Safety	Growth	Payout
Excess Returns	**1.13**	**1.08**	**0.87**	**0.78**	**0.21**
	(13.75)	(13.12)	(8.51)	(10.48)	(2.98)
CAPM-alpha	**1.20**	**1.14**	**0.95**	**0.76**	**0.30**
	(15.13)	(14.11)	(9.63)	(10.20)	(4.65)
3-factor alpha	**1.34**	**1.26**	**1.20**	**0.93**	**0.20**
	(18.65)	(17.17)	(14.41)	(14.18)	(3.67)
4-factor alpha	**1.21**	**1.15**	**0.98**	**0.79**	**0.23**
	(17.18)	(15.71)	(12.72)	(12.52)	(4.26)
MKT	**-0.10**	**-0.07**	**-0.21**	**0.05**	**-0.11**
	-(6.11)	-(3.98)	-(11.47)	(3.13)	-(8.48)
SMB	**-0.27**	**-0.29**	-0.04	**-0.18**	**-0.17**
	-(11.48)	-(11.85)	-(1.65)	-(8.55)	-(9.32)
HML	**-0.19**	**-0.16**	**-0.47**	**-0.29**	**0.25**
	-(7.32)	-(5.81)	-(16.04)	-(11.96)	(12.23)
UMD	**0.13**	**0.12**	**0.22**	**0.15**	**-0.04**
	(7.95)	(6.95)	(12.24)	(9.86)	-(2.94)
Sharpe Ratio	1.83	1.74	1.13	1.39	0.40
Information Ratio	2.40	2.21	1.78	1.75	0.58
Adjusted R2	0.45	0.35	0.51	0.45	0.32

Additionally, I investigate the role of longing and shorting of quality and junk within the QMJ factor excess returns and alphas. Figure 3 shows the cumulative returns of longing quality, along with the cumulative returns from QMJ. It can be seen that QMJ returns are made up of mostly long quality returns. However, the percentage of QMJ returns from longing quality is seen to be decreasing across the sample period while shorting junk becomes increasingly important.

Figure 3

This figure includes the cumulative returns of the long only side of QMJ, from June 1956 to December 2012, in addition to cumulative QMJ factor returns of Figure 2. The long sample of U.S. stocks contains all common stocks from the CRSP/Compustat database and the methodology for construction of QMJ follows Asness, Frazzini and Pedersen (2013).



The scenario reverses itself when controlling for the market. The CAPM alphas, which are the intercepts in a time series regression of QMJ, long quality or short junk excess returns on excess returns from the market, are reported for the entire sample period and three subperiods in Table 7. It can be seen that the majority of the QMJ alpha comes from shorting junk in all time periods, except from June 1956 to December 1969 when the long and short side contribute in a more balanced fashion to the QMJ alpha. Israel and Moskowitz (2013) observe that the SMB alpha is dominated by long positions, HML alpha comes mostly, but not entirely, from the long side as well and UMD alpha is driven equally from the long and short side. QMJ demonstrates a degree of unique behavior among all other strategies, by being dominated by the short side. This may provide a partial explanation for the premiums obtained by QMJ as shorting junk might introduce a degree of risk, while at the same time being associated weakly with prices and providing significant negative returns. The role of shorting junk in excess QMJ returns is also seen to be increasing with time.

Table 7

This table reports CAPM alphas of QMJ, the long side of QMJ i.e., quality and the short side of QMJ i.e., junk, for the full sample period (June 1956 to December 2012) of U.S. common stocks and three sub periods: June 1956 to December 1969, January 1970 to December 1989, and January 1990 to December 2012. All alphas are expressed as percent. The t statistics are reported in brackets and significance is indicated in bold.

	1956-2012	1956-1969	1970-1989	1990-2012
Quality	**0.22**	**0.30**	**0.19**	**0.20**
	(4.90)	(4.19)	(2.50)	(2.74)
Junk	**-0.98**	**-0.44**	**-0.99**	**-1.30**
	-(12.45)	-(4.52)	-(7.56)	-(9.33)
QMJ	**1.20**	**0.74**	**1.18**	**1.50**
	(15.13)	(6.44)	(9.51)	(11.06)

Now that I have studied quality and QMJ as factors and established conformance with Asness, Frazzini and Pedersen (2013), the rest of this section will be dedicated to exploring quality further, specifically in relation to the value factor, size factor and market beta. Moreover, I conduct the managed volatility analysis for QMJ in addition to the original factors studied by Moreira and Muir (2017).

Since value stocks are those with high book values but lower prices, they are dubbed underpriced and are associated with higher excess returns and alphas as shown by Fama and French (1993 and 1996). As was observed earlier, quality stocks too exhibit a similar behavior. They are stocks that may not necessarily have higher risk, owing to lower betas, but perform well in terms of higher excess returns and hence can be thought of as underpriced by the market. Quality also explained very little variation (12%) in prices. On the other hand, quality stocks are, perhaps by construction, expensive stocks and this was seen when quality was priced and a significant positive association was found. In theory, this is contrary to value, which is made up of cheap stocks.

To explore the relationship between quality and value, I do a conditional sort by first sorting my sample of stocks into ten deciles based on book to market equity and then making five quality sorted portfolios within each decile. This allows for a look at how quality behaves within value and growth portfolios.

Table 8

This table reports quality return characteristics within value portfolios for the long sample (June 1956 to December 2012) of U.S. stocks. Stocks are ranked according to book to market ratios and ten value portfolios are formed using NYSE breakpoints. Within each value portfolio, stocks are ranked according to quality scores and five quality portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from high quality stocks, low quality stocks, and the difference between high and low quality stocks are reported within each value portfolio. Sharpe ratio is the excess 5-1 return divided by the standard deviation of returns. Alpha is the intercept in a time series regression of excess 5-1 return on excess market return. The t statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent. Sharpe ratios are annualized by multiplying them with the square root of 12.

	Growth								Value	
	1	2	3	4	5	6	7	8	9	10
Quality										
Return (5-1)	**1.84**	**1.62**	**1.72**	**1.55**	**1.59**	**1.62**	**1.67**	**1.41**	**1.73**	**1.37**
	(7.47)	(8.04)	(8.87)	(7.91)	(8.77)	(8.78)	(8.85)	(7.84)	(10.05)	(6.45)
Long side	**0.77**	**0.99**	**1.11**	**1.16**	**1.30**	**1.32**	**1.39**	**1.68**	**2.10**	**2.20**
	(4.12)	(5.13)	(5.73)	(5.82)	(6.49)	(6.83)	(6.88)	(8.37)	(9.74)	(9.45)
Short side	**-1.07**	**-0.64**	**-0.61**	-0.39	-0.29	-0.30	-0.28	0.27	0.37	**0.83**
	-(3.37)	-(2.44)	-(2.34)	-(1.54)	-(1.26)	-(1.24)	-(1.19)	(1.23)	(1.63)	(3.06)
Percent long side	41.85	61.11	64.53	74.84	81.76	81.48	83.23	119.15	121.39	160.58
Sharpe Ratio	0.99	1.07	1.18	1.05	1.17	1.17	1.18	1.04	1.34	0.86
Alpha	**2.15**	**1.80**	**1.87**	**1.68**	**1.63**	**1.72**	**1.72**	**1.42**	**1.75**	**1.48**
	(9.72)	(9.34)	(10.01)	(8.79)	(8.92)	(9.47)	(9.10)	(7.81)	(10.07)	(7.02)

Table 8 presents the results of this and as can be seen, the time series average of value weighted cross sectional 5-1 return spreads (QMJ) do not exhibit a monotonically increasing or decreasing relationship. However, deciles 8, 9 and 10 (value) have a lower excess QMJ return on average of 1.50 percent, compared to the 1.73 percent of deciles 1, 2, and 3 (growth). CAPM alphas follow a similar pattern. The long and short side excess returns of the QMJ strategy, however, exhibit monotonically increasing patterns. This is an interesting result; while on the growth side, almost half of the QMJ returns come from shorting junk stocks, on the value side, more than 100% come from longing quality and shorting junk becomes increasingly insignificant. Shorting junk actually decreases the return of QMJ since junk stocks also offer positive returns on the value side. Longing value quality stocks and shorting growth junk stocks may therefore offer the best returns.

Next, I turn to the relationship between quality and size. According to Asness, Frazzini and Pedersen (2013), and as was observed earlier in the section, QMJ had a negative factor loading on SMB and is therefore, long big stocks and short small stocks. To examine quality within size, and to compare my results with the behavior of value within size, I draw inspiration from Israel and Moskowitz (2013) who analyze the role of shorting and firm size on market anomalies. First, I sort my universe of stocks into five portfolios, increasing in size based upon increasing market equity. Then, within each size portfolio, I make five portfolios increasing in book to market equity (value) and increasing in quality.

Panel A of Table 9 presents results of value within size. The 5-1 spread is long value and short growth strategy's excess returns. The monthly value weighted difference between excess returns of portfolio 5 and portfolio 1 is taken and then the time series average of these is reported. The returns decrease monotonically and are largely significant. The long side of this strategy i.e., excess returns from portfolio 5 are also reported and also decrease monotonically. It is interesting to observe that more than 100% of the returns of HML come from the long side. The percentage of returns coming from the long side of value increase as size increases. The CAPM alphas also exhibit similar behavior, except the percentage of alphas coming from the long side stays more or less consistent at approximately 80%. These results conform to those of Israel and Moskowitz (2013).

Panel B of Table 9 reports the results of conducting a similar investigation of QMJ within size. I find that the trend of decreasing excess returns and alphas as size increases is repeated here. The quality strategy offers marginally higher returns and alphas as compared to value but behaves similarly to value, within size. Most of the QMJ returns come from the long side, 85% on average. The long side contributes approximately 50%, however, to the alphas. The highest return and alpha is obtained by longing small quality stocks and shorting small junk stocks. This is expected since big stocks are safer and easier to trade and even though quality stocks are thought to be big stocks, the QMJ strategy is more profitable among smaller stocks which are riskier and offer higher return. To explore quality within size further, I look at excess returns within the profitability, growth, safety and payout strategies the results of which are reported in Table 1A in the Appendix. The highest significant results come from profitability, growth and safety. It is observed that more than 100% of the long/short strategy returns come from the long side while the short side excess returns are mostly insignificant. This is similar to the dominance of long side returns, of QMJ, observed in Figure 3 as well.

Table 9

This table reports quality and value returns characteristics within size portfolios for the long sample (June 1956 to December 2012) of U.S. stocks. Stocks are ranked according to market capitalization and five size portfolios are formed using NYSE breakpoints. Within each size portfolio, stocks are ranked according to book to market ratios and quality scores and five value and quality portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from high value and quality stocks (long side), the difference between high and low value and quality stocks (5-1 spread) are reported within each size portfolio. Alpha is the intercept in a time series regression of excess 5-1 return on excess market return and the long side is a time series regression of long side excess return on excess market return. The t statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent.

	1	2	3	4	5
	Small				Big
Panel A					
VALUE					
Returns					
5-1 spread	**1.92**	**1.28**	**0.97**	**0.64**	0.22
	(14.90)	(10.19)	(7.16)	(4.62)	(1.49)
Long side	**2.13**	**1.53**	**1.29**	**1.12**	**0.65**
	(8.50)	(6.57)	(6.25)	(5.87)	(3.91)
Percent long side	110.94	119.53	132.99	175.00	295.45
Alphas					
5-1 spread	**2.00**	**1.37**	**1.09**	**0.76**	0.29
	(15.93)	(11.14)	(8.35)	(5.82)	(1.99)
Long side	**1.60**	**0.99**	**0.78**	**0.66**	**0.24**
	(9.68)	(7.52)	(7.50)	(6.82)	(2.93)
Percent long side	80.00	72.26	71.56	86.84	82.76

Table 9

This table reports quality and value returns characteristics within size portfolios for the long sample (June 1956 to December 2012) of U.S. stocks. Stocks are ranked according to market capitalization and five size portfolios are formed using NYSE breakpoints. Within each size portfolio, stocks are ranked according to book to market ratios and quality scores and five value and quality portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from high value and quality stocks (long side), the difference between high and low value and quality stocks (5-1 spread) are reported within each size portfolio. Alpha is the intercept in a time series regression of excess 5-1 return on excess market return and the long side is a time series regression of long side excess return on excess market return. The t statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent.

	1 Small	2	3	4	5 Big
Panel B					
QUALITY					
Returns					
5-1 spread	**2.06**	**1.92**	**1.59**	**1.25**	**0.93**
	(15.54)	(14.52)	(12.40)	(10.52)	(7.26)
Long side	**1.90**	**1.59**	**1.42**	**1.17**	**0.79**
	(8.39)	(7.36)	(7.10)	(6.12)	(4.59)
Percent long side	92.23	82.81	89.31	93.60	84.95
Alphas					
5-1 spread	**2.18**	**2.06**	**1.69**	**1.31**	**0.98**
	(17.35)	(16.59)	(13.80)	(11.13)	(7.66)
Long side	**1.37**	**1.06**	**0.91**	**0.67**	**0.36**
	(10.89)	(9.89)	(10.53)	(9.01)	(4.50)
Percent long side	62.84	51.46	53.85	51.15	36.73

To examine value and quality within beta, I follow the same procedure as Table 9 and the results are reported in Table 10. Panel A reports the results for value and as for size, value behaves similarly within beta where profitability of the value strategy rises monotonically as beta increases. Again, more than 100% of the returns and alphas are from the long side of value. Therefore, value correlates positively with beta. Panel B reports the results from quality and in this case, the results vary somewhat from value. The magnitude of profitability of the quality strategy is lower compared to value and that within size. Therefore, controlling for beta reduces the returns and alphas from the quality strategy. Although QMJ and longing quality yields higher returns and QMJ yields higher alphas for high beta stocks, interestingly the alphas from the long side of quality decrease as beta increases and the percentage of alpha from the long side decreases monotonically as beta increases. This is in agreement with the earlier deduction; the contribution from shorting junk increases as risk increases while the contribution from quality decreases as risk increases. The highest alpha can therefore be obtained by longing low beta quality stocks while shorting high beta junk stocks. This is consistent with the beta anomaly.

Furthermore, a similar relationship is observed in Table 11 where I report the three and four factor alphas of QMJ within each beta portfolio and it can be seen that the alphas do not exhibit a monotonic increasing or decreasing trend but the average alphas for high beta stocks are greater than those for low beta. It is also worth noting that the alphas and returns, although lowered, remain significant within each beta portfolio. Ruomeng Liu (2018, working paper) reports that the beta anomaly absorbs the returns of other anomalies, however I find that both the value and quality strategy remain significantly profitable within each beta portfolio. The results of Ruomeng Liu (2018, working paper) may be corroborated by testing quality, value etc. within an environment where the beta anomaly is diminished using more sophisticated techniques like those used in the paper.

Table 10

This table reports quality and value returns characteristics within beta portfolios for the long sample (June 1956 to December 2012) of U.S. stocks. Stocks are ranked according to beta and five portfolios are formed using NYSE breakpoints. Within each beta portfolio, stocks are ranked according to book to market ratios and quality scores and five value and quality portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from high value and quality stocks (long side), the difference between high and low value and quality stocks (5-1 spread) are reported within each beta portfolio. Alpha is the intercept in a time series regression of excess 5-1 return on excess market return and the long side is a time series regression of long side excess return on excess market return. The t statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent.

	1	2	3	4	5
	Low Beta			High Beta	
Panel A					
VALUE					
Returns					
5-1 spread	**0.69**	**0.51**	**0.44**	**1.04**	**1.94**
	(3.56)	(3.38)	(3.05)	(2.25)	(2.28)
Long side	**0.95**	**0.88**	**1.00**	**1.43**	**2.56**
	(4.16)	(3.42)	(2.63)	(6.36)	(8.53)
Percent long side	137.41	173.67	229.65	137.44	131.73
Alphas					
5-1 spread	**0.71**	**0.49**	**0.46**	**1.05**	**1.92**
	(4.24)	(3.31)	(2.76)	(6.38)	(8.40)
Long side	**0.84**	**0.53**	**0.53**	**0.77**	**1.54**
	(5.69)	(4.28)	(4.17)	(5.38)	(6.63)
Percent long side	118.12	108.24	114.48	73.13	80.25

Table 10

This table reports quality and value returns characteristics within beta portfolios for the long sample (June 1956 to December 2012) of U.S. stocks. Stocks are ranked according to beta and five portfolios are formed using NYSE breakpoints. Within each beta portfolio, stocks are ranked according to book to market ratios and quality scores and five value and quality portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from high value and quality stocks (long side), the difference between high and low value and quality stocks (5-1 spread) are reported within each beta portfolio. Alpha is the intercept in a time series regression of excess 5-1 return on excess market return and the long side is a time series regression of long side excess return on excess market return. The t statistics are reported in brackets and significance is indicated in bold. Returns and alphas are in monthly percent.

	1	2	3	4	5
	Low Beta			High Beta	
Panel B					
QUALITY					
Returns					
5-1 spread	**0.89**	**0.81**	**1.14**	**0.92**	**1.41**
	(6.68)	(6.10)	(7.70)	(6.10)	(7.98)
Long side	**0.55**	**0.71**	**0.94**	**0.87**	**1.28**
	(4.78)	(4.93)	(4.99)	(3.45)	(3.45)
Percent long side	61.80	87.65	82.46	94.57	90.78
Alphas					
5-1 spread	**0.87**	**0.81**	**1.17**	**0.95**	**1.53**
	(6.48)	(6.11)	(7.83)	(6.29)	(8.90)
Long side	**0.42**	**0.39**	**0.41**	**0.22**	**0.32**
	(3.97)	(4.39)	(5.30)	(2.10)	(2.13)
Percent long side	48.28	48.15	35.04	23.16	20.92

Table 11

This table reports alphas of quality within size and beta for the long sample (June 1956 to December 2012) of U.S. stocks. Stocks are ranked according to market capitalization and beta and five portfolios are formed using NYSE breakpoints. Within each size and beta portfolio, stocks are ranked according to their quality scores and five quality portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from the difference between high and low quality stocks (5-1 spread) are found within each size and beta portfolio. Alpha is the intercept in a time series regression of excess 5-1 return on excess market return, SMB, HML and UMD. The t statistics are reported in brackets and significance is indicated in bold. Alphas are in monthly percent.

	1	2	3	4	5
Panel A	Small			Big	
QMJ					
3-factor alpha	**2.29**	**2.17**	**1.81**	**1.48**	**1.20**
	(18.92)	(17.74)	(14.90)	(13.01)	(9.95)
4-factor alpha	**2.10**	**1.94**	**1.57**	**1.25**	**0.96**
	(17.47)	(16.24)	(13.31)	(11.31)	(8.21)
Panel B	Low Beta			High Beta	
QMJ					
3-factor alpha	**1.08**	**0.98**	**1.36**	**1.16**	**1.80**
	(8.57)	(7.59)	(9.54)	(8.06)	(11.27)
4-factor alpha	**1.01**	**0.92**	**1.20**	**1.06**	**1.55**
	(7.79)	(7.00)	(8.31)	(7.19)	(9.78)

Having observed quality within value, size and beta, I now turn to the volatility managed portfolios of Moreira and Muir (2017). First, I replicate their volatility managed market, size, value and momentum factors and my findings in Table 12 and Table 1B conform, almost exactly, to the paper. Table 12 reports the coefficients and alphas from running a regression of the managed factor excess returns on the raw factor excess returns. All the coefficients are positive and significant, showing that the managed factor returns increase as the raw returns increase. I find that QMJ behaves in a similar manner and shows the highest significant regression coefficient. The alphas are positive for the market, value and momentum while they are significant for only market and momentum. The managed volatility momentum factor performs the best with the highest alphas and this is attributed to avoiding momentum crashes by adjusting for volatility. I find that the alpha for quality is positive and significant but lower than momentum and the market. Therefore, managing volatility somewhat improves the profitability of the quality strategy. Panel B also reports the alphas from regressions controlling for the Fama and French factors. Moreira and Muir (2017) discuss the intuition of the positive alphas as a result of the managed volatility factor taking advantage of the higher price of risk during low risk times, by increasing the exposure of the factor and avoiding higher risk by decreasing exposure.

Since the standard deviation of both managed and raw factor returns are equal by construction, the Sharpe ratio will reflect the difference in excess returns between the two. I report time series averages of the Sharpe ratios of both managed and raw factors in Table 13, along with the differences between them. The Sharpe ratios of the market, momentum and quality improve by managing volatility while those of size and value decrease, with value decreasing only marginally compared to the higher decrease associated with managing volatility of size. However, the difference between the Sharpe ratios is only statistically different from 0 for the momentum factor and is insignificant for all others factors.

Table 1B in the Appendix reports some additional results from running time series regressions of the raw factor returns on the realized variance in the previous month. The coefficients of realized variance are reported. This provides another perspective and look at the relationship between risk and return of each factor and whether a higher realized variance in the previous month predicts higher returns. The results indicate that such a relationship doesn’t exist as the coefficients are not significant. The same results are observed for QMJ. Moreira and Muir (2017) credit this phenomenon to be the reason why their managed portfolios provide a positive alpha since volatility doesn’t predict higher returns and therefore, high volatility is an indicator of a poor risk return tradeoff and decreasing exposure works.

Table 12

This table reports volatility managed factor alphas. The market, size, value and momentum excess returns sample runs from January 1927 to December 2015 while the QMJ excess return sample runs from August 1957 to December 2015. A time series regression of each volatility managed factor return is run on the raw factor return. The coefficient of the raw factor and the intercept are reported. T statistics are reported in brackets and significance is indicated in bold. All factors are annualized in percent per year by multiplying them by 12.

Panel A	1	2	3	4	5
	mMkt	mSMB	mHML	mMom	mQMJ
Mktrf	**0.61**				
	(25.10)				
SMB		**0.61**			
		(25.14)			
HML			**0.57**		
			(22.65)		
Mom				**0.47**	
				(17.36)	
QMJ					**0.64**
					(22.26)
Alpha	**4.78**	-0.50	1.80	**12.55**	**1.76**
	(3.01)	-(0.53)	(1.68)	(8.08)	(2.19)
R2	0.37	0.37	0.32	0.22	0.41
Panel B					
Alpha	**5.35**	-0.27	**2.48**	**10.52**	**2.68**
	(3.39)	-(0.28)	(2.36)	(6.71)	(3.16)

Table 13

This table reports the Sharpe ratios of the volatility managed and raw factors along with the difference between them. The market, size, value and momentum excess returns sample runs from January 1927 to December 2015 while the QMJ excess return sample runs from August 1957 to December 2015. Sharpe ratio is calculated as the time series average of the monthly percent excess factor return divided by the standard deviation in excess return of that factor. T statistics are reported and significance is indicated in bold.

	Sharpe Ratio	Difference	Difference t-stat
Mkt	0.41		
mMkt	0.51	0.09	(1.00)
SMB	0.23		
mSMB	0.10	-0.14	-(1.45)
HML	0.38		
mHML	0.36	-0.02	-(0.15)
Mom	0.50		
mMOM	1.00	**0.50**	(4.56)
QMJ	0.52		
mQMJ	0.56	0.04	(0.33)

5. Conclusion

In conclusion, quality presents a puzzle; it should command higher prices as a consequence of its construction. However, the factor's price relationship is weak and simultaneously, it provides higher returns. Therefore, it becomes an anomaly where significant abnormal returns can be obtained by going long quality stocks and shorting junk stocks. The construction of quality itself has varied over time and across research, the unique way in which profitability, growth, safety and payout are combined serves to make QMJ returns higher than all quality components in isolation. The components show a marginally higher effect on prices and consequently hold lower abnormal returns as strategies. QMJ shows a negative correlation with the market, size and value and I take a closer look at this by conditionally sorting quality within value, size and market beta.

The main results of this exercise include the finding that QMJ alphas are dominated by the short side i.e, shorting junk stocks. The role of shorting in QMJ excess returns is also found to be increasing with time. This plays a part in the profitability of QMJ, which is consistent with the largely unexplained relationship of quality and prices. I conclude that shorting junk stocks is inherently risky, combined with the significant negative returns associated with junk, and thus it contributes to the significant premiums associated with QMJ.

I find evidence in favor of value and quality being hedges for each other, as a result of value consisting of cheaper stocks and quality consisting of more expensive stocks. It is observed that combining the two strategies leads to higher premiums, specifically through longing value quality stocks and shorting growth junk stocks. I also observe a strong size effect when sorting quality within size, as the quality premium decreases monotonically with size. Higher premiums are found to be associated with longing small quality stocks and shorting small junk stocks. This is also partially a result of the returns from junk increasing as size increases.

Although it seems that quality stocks may be mispriced, a risk explanation still cannot be ruled out completely. I observe that controlling for beta lowers quality premiums. I also find that the performance of quality within risk shows higher and significant returns of quality among high beta stocks but on the other hand, shows lower alphas of quality among high beta stocks. Evidence for the beta anomaly is found, as higher profits are found to be obtained from longing low beta quality stocks and shorting high beta junk stocks. Lastly, I find that managing the volatility of QMJ, by increasing returns as realized return volatility decreases and decreasing them as volatility increases, leads to a marginal improvement in the performance of QMJ.

The quality factor remains a puzzle for asset pricing and there are a number of research avenues that may be explored further. The construction of payout, as a quality component, can be changed to reflect a shorter term high dividend yield instead of a five year growth of net payout. The relationship of quality with momentum may be studied and compared with value, which shows a negative correlation with the momentum factor. Also, the effect of muting the beta anomaly on the performance of quality will provide interesting insights into its risk return relationship.

References

Asness, C.S., Frazzini A., and Pedersen L.H. (2013), "Quality Minus Junk," working paper, AQR Capital Management.

Ohlson, J.A. (1980), "Financial Ratios and the Probabilistic Prediction of Bankruptcy," Journal of Accounting Research 18(1), 109-131.

Altman, E.I. (1968), "FINANCIAL RATIOS, DISCRIMINANT ANALYSIS AND THE PREDICTION OF CORPORATE BANKRUPTCY," The Journal of Finance 23(4), 589-609.

Mohanram, P.S. (2005), "Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis," Review of Accounting Studies 10(2-3), 133-170.

Black, F., Jensen, M.C., and Scholes, M. (1972), "The Capital Asset Pricing Model: Some Empirical Tests." In Michael C. Jensen (ed.), Studies in the Theory of Capital Markets, New York, pp. 79-121.

George, T.J. and Hwang, C-Y. (2010), "A resolution of the distress risk and leverage puzzles in the cross section of stock returns," Journal of Financial Economics 96(1), 56-79.

Novy-Marx, R. (2013), "The Other Side of Value: The Gross Profitability Premium," Journal of Financial Economics 108(1), 2013, 1-28.

Frazzini, A. and Pedersen, L.H. (2013), "Betting Against Beta", Journal of Financial Economics 111(1), 1-25.

Israel, R. and Moskowitz, T.J. (2013), "The role of shorting, firm size, and time on market anomalies," Journal of Financial Economics 108(2), 275-301.

Moreira, A. and Muir, T. (2017), "Volatility-Managed Portfolios," The Journal of Finance 72(4), 1611-1644.

Banz, R.W. (1981), "The relationship between return and market value of common stocks," Journal of Financial Economics 9(1), 3-18.

Fama, E.F. and French, K.R. (1992), "The Cross-Section of Expected Stock Returns," The Journal of Finance 47(2), 427-465.

Stattman, D. (1980), "Book Values and Stock Returns," The Chicago MBA: A Journal of Selected Papers 4, 9-17.

Rosenberg, B., Reid, K., and Lanstein, R. (1985), "Persuasive Evidence of Market Inefficiency," Journal of Portfolio Management 11, 9-17.

DeBondt W.F.M. and Thaler, R. (1985), "Does the Stock Market Overreact?," The Journal of Finance 40(3), 793-805.

Lakonishok, J., Shleifer, A., and Vishny, R.W. (1994), "Contrarian Investment, Extrapolation, and Risk," The Journal of Finance 49(5), 1541-1578.

Frankel, R. and Lee, C. (1998), "Accounting valuation, market expectation, and cross-sectional stock returns," Journal of Accounting and Economics 25(3), 283-319.

Piotroski, J. (2000), "Value investing: The use of historical financial statement information to separate winners from losers," Journal of Accounting Research 38, 1-41.

Chan, L.K.C., Hamao, Y., and Lakonishok, J. (1991), "Fundamentals and Stock Returns in Japan," The Journal of Finance 46(5), 1739-1764.

Hawawini, G. and Keim, D.B. (1995), "Chapter 17 On the predictability of common stock returns: World-wide evidence," Handbooks in Operations Research and Management Science 9, 497-544.

Fama, E.F. and French, K.R. (1998), "Value versus Growth: The International Evidence," The Journal of Finance 53(6), 1975-1999.

Fama, E.F. and French, K.R. (2012), "Size, value, and momentum in international stock returns," Journal of Financial Economics 105(3), 457-472.

Liu, R. (2018), "Asset Pricing Anomalies and the Low-risk Puzzle," working paper.

Fama, E.F. and French, K.R. (1993), "Common risk factors in the returns on stocks and bonds," Journal of Financial Economics 33, 3-56.

Fama, E. F. and French, K. R. (1996), "Multifactor Explanations of Asset Pricing Anomalies," The Journal of Finance 51(1), 55-84.

Newey, W. and West, K. (1987), "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," Econometrica 55(3), 703-708.

Appendix A1

Profitability Measures:

GPOA = (Total revenue – Cost of goods sold) / Total assets

ROE = Net income / Book equity

ROA = Net income / Total assets

CFOA = (Net income + Depreciation – Changes in working capital – Capital expenditures) / Total assets

GMAR = (Total revenue – Cost of goods sold) / Total sales

ACC = (Depreciation – Changes in working capital) / Total assets

WC (Working capital) = Current assets – Current liabilities – Cash and short term instruments + Short

term debt + Income taxes payable

BE (Book equity) = Shareholders’ equity – Preferred stock[5]

If shareholders’ equity isn’t available, the following is used.

SEQ (Shareholders’ equity) = Common equity + Preferred Stock

If both shareholders’ equity and common stock aren’t available, the following proxy is used.

SEQ (Shareholders’ equity) = Total assets – (Total liability + Minority Interest)

[5] For preferred stock value, I use PSTKRV, PSTKL or PSTK, from the CRSP/Compustat merged database, depending on availability.

Growth Measures:

ΔGPOA = (GP_t – GP_{t-5}) / Total $assets_{t-5}$ where gross profit (GP) = Total revenue – Cost of goods sold.

ΔROE = (Net $income_t$ – Net $income_{t-5}$) / Book $equity_{t-5}$

ΔROA = (Net $income_t$ – Net $income_{t-5}$) / Total $assets_{t-5}$

ΔCFOA = (CF_t – CF_{t-5}) / Total $assets_{t-5}$ where cash flow (CF) = Net income + Depreciation – Changes in working capital – Capital expenditures.

ΔGMAR = (GP_t – GP_{t-5}) / Total $sales_{t-5}$

ΔACC = ($MWCPD_t$ – $MWCPD_{t-5}$) / Total $assets_{t-5}$ where MWCPD = Depreciation – Changes in working capital.

Safety Measures:

BAB = - 1 * (Rolling one year standard deviation of excess stock return / Rolling standard deviation of

excess market return) * Rolling five year correlation of stock and market

IVOL = - 1 * (Rolling one year standard deviation of beta adjusted excess stock return)

LEV = - 1 * (Long term debt + Short term debt + Minority interest + Preferred stock) / Total assets

O = - 1 * (-1.32 – 0.407*log (Adjasset / Consumer price index) + 6.03*(Book value of debt[6]/Adjasset) – 1.43*((Current assets – Current liabilities)/Adjasset) + 0.076*(Current liabilities/Current assets) – 1.72*OENEG – 2.37*(Net income/Total assets) – 1.83*(Pretax income/Total liabilities) + 0.285*INTWO – 0.521*CHIN)
where Adjasset (Adjusted total assets) = Total assets + 0.1*(Market equity - Book equity), OENEG is a dummy equal to one when total liabilities are greater than total assets, INTWO is a dummy equal to one when net income is negative for the current and previous fiscal year, and CHIN is changes in net income and is calculated as (Net income – Net income$_{t-1}$) / (|Net income|$_t$ + |Net income|$_{t-1}$)

AltZ = (1.2*Working capital + 1.4*Retained earnings + 3.3*Earnings before interest and taxes + 0.6*Market equity + Total sales) / Total assets

EVOL = Standard deviation of annual ROE over the past five years

Payout Measures:

EISS = - 1*log (Split adjusted shares outstanding$_t$ / Split adjusted shares outstanding$_{t-1}$)

DISS = - 1*log (Total debt$_t$ / Total debt$_{t-1}$) where Total debt = Long term debt + Short term debt + Minority interest + Preferred stock.

NPOP = (Total net payout$_t$ – Total net payout$_{t-5}$) / (Total profits$_t$ = Total profits$_{t-5}$) where Total net payout = Net income – Changes in book equity and Total profits = Total revenue – Cost of goods sold

[6] Book value of debt is DLC + DLTT.

Appendix A2

The original paper reports 19,356 stocks in their US sample. I start with 23,259 stocks and end up with 9,291 stocks in my sample. It is possible that my universe of stocks is much smaller than the paper's due to the manipulations that I've conducted. This may have resulted in the higher returns and alphas observed during the analysis.

The construction of quality, even though followed as closely as possible, may have differed as it includes the calculation of more than twenty individual variables. The only intentional departure is within safety's betting against beta variable where I use monthly as opposed to daily observations, idiosyncratic volatility variable where I again use monthly as opposed to daily observations, and earnings volatility variable where I use annual instead of quarterly data.

Another avenue which may have resulted in the differences in observations is the value weighting mechanism. It is not explicitly stated in the paper and I try value weighting with current market capitalization, June market capitalization, one year lagged market capitalization and one month lagged market capitalization. The lagged one month market capitalization provided the closest results and it is used throughout the analysis of the QMJ paper.

Finally, the construction of tables may have differed through minute differences in the methods used to obtain the time series of averages of cross sectional observations, running robust regressions and so on.

Table 1A

This table reports the excess returns and long side returns of each quality component strategy for the long sample (June 1956 to December 2012) of U.S. common stocks. Stocks are ranked according to market capitalization and five size portfolios are formed using NYSE breakpoints. Within each size portfolio, stocks are ranked according to quality component scores and five component portfolios are formed using NYSE breakpoints. Portfolios are value weighted and rebalanced every calendar month to maintain value weights. The time series average of value weighted cross sectional excess returns from high component score (long side), the difference between high and low component score (5-1 spread) are reported within each size portfolio. The t statistics are reported in brackets and significance is indicated in bold. Returns are in monthly percent.

	1	2	3	4	5
	Small				Big
Profitability	**2.01**	**1.84**	**1.50**	**1.28**	**0.84**
	(15.07)	(13.91)	(12.04)	(10.80)	(6.41)
Long side	**1.97**	**1.55**	**1.37**	**1.18**	**0.7**
	(8.53)	(7.04)	(6.72)	(6.01)	(3.99)
Short side	-0.05	-0.29	-0.52	-0.10	-0.14
	-(0.16)	-(1.05)	-(0.52	-(0.42)	-(0.72)
Growth	**1.48**	**1.39**	**1.08**	**0.99**	**0.56**
	(14.72)	(12.55)	(9.67)	(8.61)	(4.25)
Long side	**1.84**	**1.61**	**1.33**	**1.18**	**0.76**
	(7.44)	(6.79)	(5.87)	(5.32)	(3.83)
Short side	0.36	0.22	0.25	0.19	0.19
	(1.31)	(0.87)	(1.09)	(0.88)	(1.12)
Safety	**1.57**	**1.55**	**1.38**	**1.15**	**0.71**
	(8.91)	(9.58)	(8.99)	(7.83)	(4.82)
Long side	**1.69**	**1.43**	**1.36**	**1.19**	**0.68**
	(7.30)	(6.68)	(6.93)	(6.54)	(4.30)
Short side	0.12	-0.12	-0.02	0.04	-0.04
	(0.41)	-(0.44)	-(0.07)	(0.16)	-(0.18)
Payout	**0.23**	0.18	**0.34**	0.12	0.15
	(2.12)	(1.54)	(2.86)	(1.11)	(1.28)
Long side	**1.14**	**0.91**	**0.90**	**0.78**	**0.57**
	(4.85)	(4.22)	(4.57)	(4.01)	(3.40)
Short side	**0.91**	**0.73**	**0.56**	**0.66**	**0.43**
	(3.37)	(2.87)	(2.36)	(2.92)	(2.19)

Table 1B

This table reports the coefficients on volatility in a time series regression of raw factor returns on the realized volatility in the past month for each factor. The market, size, value and momentum excess returns sample runs from January 1927 to December 2015 while the QMJ excess return sample runs from August 1957 to December 2015. T statistics are also reported in brackets.

	1	2	3	4	5
	Mkt	SMB	HML	Mom	QMJ
vMkt	-0.04				
	-(0.10)				
vSMB		0.10			
		(0.58)			
vHML			0.56		
			(1.12)		
vMom				-0.68	
				-(1.86)	
vQMJ					0.12
					(0.51)