Norwegian School of Economics
Bergen, Fall 2018

The Effect of Sector Quality in Quality Minus Junk

The Quality Puzzle Deepens

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Acknowledgements

We would like to express our appreciation and thanks to our supervisor, Francisco Santos, for his invaluable guidance during the process of writing this thesis. Whenever we ran into trouble, the door to his office was always open. Also, we would like to thank the IT-department at NHH for giving us access to software which has been very useful to us.

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Abstract

In this thesis we test whether sector quality effects drive the abnormal returns of the Quality Minus Junk (QMJ) strategy. We find that the strategy makes involuntarily sector bets, as it invests in outperforming sectors rather than individual quality stocks. This implies that sector quality effects partially drive the QMJ abnormal returns. A consequence of the sector quality effects is lack of diversification in the QMJ strategy.

Having established that sector quality effects partially drive QMJ abnormal returns, we create a sector neutral QMJ that is restricted to how aggressively it can invest in sectors. This strategy is more diversified than the unrestricted QMJ but does not match its performance in terms of abnormal returns and Sharpe ratio. We volatility-manage the sector neutral strategy and find that it yields significant abnormal returns and Sharpe ratio of the same magnitude as the unrestricted QMJ strategy. In other words, the volatility-managed strategy does not bet on outperforming sectors, and still performs well in return tests. Therefore, the QMJ abnormal returns cannot be explained by sector quality effects, and the quality puzzle deepens.

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1. Introduction

In recent years, the asset pricing anomaly of quality investing has been researched extensively. Investors earn high abnormal returns by buying profitable, safe and growing stocks, and selling stocks that are unprofitable, unsafe and not growing. However, researchers fail to agree upon a risk-based explanation for these abnormal returns. How can safe, profitable and growing firms be riskier than firms that are unsafe, unprofitable and not growing? Asness, Frazzini and Pedersen (2017) define three main components of stock quality that investors should be willing to pay higher prices for; profitability, safety and growth. In a risk-reward universe, higher prices should mechanically result in lower expected returns. Therefore, the abnormal return of quality stocks is an asset pricing puzzle.

Asness et al. find quality measures within profitability, safety and growth in the extensive literature on the quality anomaly and combine them into one composite quality measure. They proceed to create Quality Minus Junk (QMJ), a strategy that is long high-quality stocks and short low-quality stocks. In return tests, QMJ delivers positive significant abnormal returns, even when controlling for a 6-factor model. It has negative market, value and size loadings, which suggests the strategy is not exposed to the traditional risk factors. Furthermore, the QMJ strategy benefits from flight to quality, meaning investors flock to quality stocks during market turmoil. This adds to the puzzle of quality stocks returning positive excess returns and alphas.

In this thesis we seek to further understand the quality puzzle. We hypothesize that the abnormal returns of the QMJ strategy are driven by sector outperformance rather than individual stock quality. We refer to this as sector quality effects. Firms within sectors tend to be more correlated than firms across the entire investment space, meaning such a strategy might suffer from lack of diversification. If the QMJ strategy invests aggressively in particular sectors, this makes the quality puzzle less of a puzzle.

To begin, we replicate the U.S. QMJ strategy returns of Asness et al. (2017). We find a monthly 6-factor alpha for QMJ of 0.22% compared to 0.30% in the original paper. The replicated QMJ strategy bets on low beta, big, low book-to-market, profitable and aggressive stocks, which follows the same pattern as the original QMJ. These results suggest we successfully replicate the QMJ strategy.

In the second part of the thesis, we follow the methodology of Moskowitz and Grinblatt (1999) to test whether sector quality effects drive the QMJ abnormal returns. First, we compute the QMJ strategy returns within each sector. We find that the QMJ strategy within each sector fails to produce significant abnormal returns in eight out of ten sectors in the 6-factor model. This suggests the QMJ bets on sector outperformance, as it is not consistently long the quality stocks and short the junk stocks in each sector throughout the sample.

Next, we assess the performance of the QMJ strategy after demeaning the quality score of each individual stock with the average monthly sector quality score. This allows us to asses individual stock quality as a driver of returns to a greater extent. Our findings suggest that demeaning does not affect the abnormal returns, excess returns or volatility of the QMJ strategy. This is an indication of sector quality effects not being present in the QMJ.

We proceed to create random sector portfolios, where we replace stocks in a sector with stocks that have approximately the same quality score, regardless of sector. This means we reshuffle the sector composition without changing the quality composition of the sectors. If sector quality effects are the only driver of QMJ abnormal returns, we expect the random sectors to not exhibit significant alphas. We document significant abnormal returns for four out of ten sectors in the 6-factor model, which indicates sector quality effects are not the only driver of QMJ abnormal returns.

Furthermore, we create portfolios that are long the low-quality stocks from the sectors scoring highest on quality and short the high-quality stocks from the sectors scoring lowest on quality. On average, low-quality stocks in the high-quality sectors scores lower on quality than high-quality stocks in the low-quality sectors. We find that these portfolios deliver positive alphas, even though we buy stocks of lower quality than the ones we sell. As we expect junk stocks to perform worse than quality stocks if individual stock quality is the driver of QMJ abnormal returns, this strongly indicates sector quality effects driving QMJ abnormal returns.

As a final test, we create a QMJ strategy with restrictions to how aggressively it invests in sectors – a sector neutral QMJ. If the restricted QMJ performs worse than the unrestricted QMJ in return tests, it suggests that outperforming sectors drive the abnormal returns of the QMJ strategy. We find that a sector neutral QMJ strategy delivers an insignificant monthly 6-factor alpha of 0.09%, substantially lower than the abnormal returns of the unrestricted QMJ.

A majority of the tests point towards there being sector quality effects within the QMJ factor. The *within-sector*, *long junk – short quality*, and *sector-neutral QMJ* tests indicate sector quality effects drive QMJ abnormal returns. The *random sector* test suggests sector quality effects are not the only driver of abnormal returns, while the *sector demeaning* test indicate sector quality effects are not present. Due to the contradicting result from the *sector demeaning* test and the *random sector* test, we cannot conclude that only sector quality effects drive the QMJ abnormal returns. Therefore, our research suggests sector quality effects partially drive QMJ abnormal returns, which might serve as a potential explanation of the quality puzzle.

To challenge the potential explanation of the quality puzzle, we use the sector neutral QMJ as a starting point. The strategy is more diversified than the unrestricted QMJ but does not yield significant abnormal returns. However, research from Moskowitz and Daniel (2016) and Barroso and Santa-Clara (2015) show that strategy returns can be enhanced and improved by volatility-management. If a volatility-managed sector neutral QMJ strategy delivers high alpha and Sharpe ratio, lack of diversification in the unrestricted QMJ cannot explain the abnormal returns of QMJ and the quality puzzle remains a puzzle.

Following the methodology of Barroso and Santa-Clara (2015), we create a variance forecast based on the volatility of daily sector neutral QMJ returns. We set a volatility target and scale our exposure to the sector neutral QMJ strategy accordingly. The volatility-managed sector neutral QMJ exhibits significant 6-factor alpha of 0.40% per month with an annual volatility target of 12%. Excess returns and Sharpe ratio drastically increase compared to the sector neutral QMJ. Since the volatility-managed sector neutral QMJ strategy does not suffer from lack of diversification but still performs well in returns tests, the quality puzzle cannot be explained by sector quality effects.

In this thesis, we contribute to the existing literature on the quality anomaly. We extend the research of Asness et al. (2017) on QMJ, attempting to find a possible explanation of the abnormal returns of the strategy. This is related to literature on how industry effects and sector effects can explain the cross-section of expected returns. Moskowitz and Grinblatt (1999) show that industry momentum drives the abnormal returns of an individual momentum strategy. On the other hand, Asness, Porter and Stevens (2000) show that by utilizing other momentum holding periods and a narrow industry definition, individual stock momentum has predictive power for the firm's stock return beyond that of industry momentum. This thesis utilizes the research of Moskowitz and Grinblatt, as we apply their methodology to the QMJ strategy. We find that sector bets partially drive the abnormal returns of the QMJ strategy. Aware of Asness et al.'s critique, we also conduct an analysis for a 48-industry sort. The results of the industry sort show that our result to a narrow industry definition.

This thesis is also related to the literature on volatility-management of factor strategies. Moskowitz and Daniel (2016) show that a dynamic momentum strategy which utilizes mean and variance forecasts of momentum nearly doubles alpha and Sharpe ratio compared to a plain momentum strategy. They study the systematic risk of momentum. On the other hand, Barroso and Santa-Clara (2015) study momentum specific risk and find it to be time-varying and predictable. Scaling a momentum strategy accordingly greatly reduces crash risk and nearly doubles Sharpe ratio. The authors claim this removes forward-looking bias. Following Barroso and Santa-Clara (2015), we show how a sector neutral QMJ strategy can be volatility-managed. We use volatility-management to prove how lack of diversification in the QMJ cannot explain the quality puzzle.

In summary, we complement the existing literature by documenting that sector quality effects partially drive QMJ abnormal returns. However, we also find that this cannot explain quality puzzle, as a volatility-managed QMJ that is not allowed to bet on sectors delivers positive abnormal returns. Thus, our thesis further deepens the quality puzzle.

The rest of the thesis is organized as follows. In Chapter 2, we present literature that is relevant to this thesis. Chapter 3 outlines our replication of the Quality Minus Junk factor. Chapter 4 contains a presentation of our methodology and results from the tests for sector quality effects within QMJ. In Chapter 5, we present the volatility-managed sector neutral QMJ portfolios. Chapter 6 analyses the robustness of our results using 48 industries instead of ten sectors. Finally, in Chapter 7 we provide the conclusion of this thesis.

2. Literature Review

Quality Minus Junk builds on a large literature of asset pricing anomalies within the quality investing universe. Asness et al. (2017) unifies these anomalies into QMJ, capturing all elements of quality in one measure. From the Gordon Growth model, Asness et al. specify three quality characteristics that should command higher prices for a stock; profitability, growth and safety. Investors should be willing to pay more for stocks exhibiting these characteristics.

Novy-Marx (2013) documents that profitable firms generate significantly higher returns than unprofitable firms and introduces gross profits-to-assets as the most powerful quality measure to explain the variation in the cross-section of expected returns. Furthermore, stocks with low beta has proven to produce high alphas (Frazzini and Pedersen, 2014), and Mohanram (2005) reports growing stocks outperform those who experience little or no growth. These are just examples of the literature available on the three quality characteristics within the QMJ. Asness et al. show that the composite QMJ strategy earns a 6-factor alpha of 0.30% on average per month. This thesis confirms these results, as we find that the QMJ strategy yields a 6-factor alpha of 0.22% on average per month.

Many have tried to explain the abnormal returns of quality stocks. Frazzini and Pedersen (2014) show how leverage-constrained investors systematically buy high-beta stocks in order to reach performance benchmarks. Consequently, high beta stocks are overbought while lack of demand for low beta stocks lowers prices and increases future expected returns. Furthermore, investors prefer stocks that exhibit lottery-like behaviour, a trait which is enhanced in economic downcycles (Kumar, 2009). Such investor behaviour can explain the lack of attention given to quality stocks.

Another approach is to explain the quality anomaly from a statistical perspective. Harvey, Liu and Zu (2015) argue that extensive data mining is conducted in asset pricing research, as “hundreds of papers and factors attempt to explain the cross-section of expected returns”. A normal t-stat criterion of 2 is therefore not suitable, and they propose a higher hurdle of at least 3. However, the hurdle is not high enough to deem the QMJ abnormal returns insignificant, neither in the original paper or in the replication part of this thesis.

Others attempt to provide risk-based explanations for the quality anomaly. This has proved to be a challenge, as profitable, safe and growing companies are associated with low risk. Additionally, Asness et al. (2017) find that quality stocks are attractive to investors in market downturns, a phenomenon they dub "flight to quality". Fama and French (2006) contribute to the risk-based explanation of the quality puzzle and show how the profitability aspect of quality is related to the cross-section of expected returns via the dividend discount model. They document that high expected profitability mechanically predicts high expected returns. Moreover, Khan (2008) presents a risk-based explanation for the accrual anomaly, as firms with high accruals often are experiencing financial distress. The accruals anomaly is utilized within profitability in the QMJ framework. In this thesis, we contribute to the literature on the quality puzzle by attempting to understand the QMJ abnormal returns from a risk perspective.

To understand the quality puzzle, we test whether the QMJ strategy invests in sector outperformance rather than individual quality stocks. This relates to literature on sector and industry effects within factor strategies. Moskowitz and Grinblatt (1999) find that industry momentum is the driver of abnormal returns of the momentum strategy. Asness, Porter and Stevens (2000) criticize the methodology of Moskowitz and Grinblatt and claim their industry definition will result in widely different businesses within the same industries. This might hide the importance of differences from industry means. They suggest sorting stocks into 48 instead of 20 industries, and show that individual stock momentum has predictive power for a firm's stock return beyond industry momentum. This thesis applies the research of Moskowitz and Grinblatt, and we use their methodology to test for sector quality effects within QMJ. However, we run robustness test for our analysis of sector effects within the QMJ and perform the same analysis for a 48-industry sort. The results of the 48-industry sort prove that our sector results are robust to a narrow industry definition.

This thesis contributes to the understanding of the role of sectors and industries within asset pricing and the financial markets. There is extensive literature showing the relatively small effect industries has on asset prices. Griffin and Karolyi (1998) find that only a small amount of the variation in country index returns can be explained by their industrial composition. Heston and Rouwenhorst (1994) document that industrial structure explains very little of the cross-sectional difference in country return volatility. On the other hand, Roll (1992) finds that each country's industrial structure is important in explaining stock price movements. While these papers research the unconditional effect of industries on the cross-section of expected returns, we examine the conditional effect of sectors within the quality anomaly. We find evidence of the original QMJ strategy being aggressively invested in sectors, which resembles the results of Roll, as sectors are in this case important in explaining stock price movements within the quality anomaly.

This thesis is also related to the literature on volatility-management of factor strategies. Moskowitz and Daniel (2016) show how forecasting mean and variance of a plain momentum strategy to scale strategy exposure nearly doubles alpha and Sharpe ratio. They use the systematic risk of momentum as a tool to scale strategy exposure. On the other hand, Barroso and Santa-Clara (2015) use momentum specific risk as a tool to scale strategy exposure. They find momentum specific risk to be time-varying and predictable, which allows them to scale the momentum strategy without forward-looking bias. The volatility-managed strategy of Barroso and Santa-Clara exhibits greatly reduced crash risk, and doubles Sharpe ratio. Volatility-managed momentum is therefore a much greater puzzle than regular momentum. Furthermore, Moreira and Muir (2017) document how changes in volatility are not followed by proportional changes in expected returns for a selection of factor strategies, such as profitability and value. They volatility-manage the factors and document improved Sharpe ratios.

As a contribution to the existing literature on volatility-management of factor strategies, we investigate the effect of volatility-management within the quality investing space. We show that the work of Barroso and Santa-Clara (2015) is applicable to the QMJ anomaly. Similarly to the momentum puzzle, volatility-management deepens the quality puzzle. We document that sector quality effects partially drive QMJ abnormal returns, but a volatility-managed sector neutral QMJ strategy yields abnormal returns in the same magnitude of the original QMJ. This thesis therefore contributes to the understanding of the quality anomaly by deepening the puzzle.

3. Replication of Quality Minus Junk

In the following chapter we present our replication of the Quality Minus Junk strategy by Asness et al. (2017).

3.1 Data

In this section we describe our data sources, data cleaning process, and computation of the quality measures described in the original paper. Using these quality measures, we construct quality-sorted portfolios and QMJ factor returns similar to those in the original paper. We follow the original paper as closely as possible and highlight potential deviations.

3.1.1 Data Sources and Quality Measures

The sample runs from July 1963 through December 2016 and contains US stocks only. Monthly stock returns are downloaded from the Center for Research on Security Prices (CRSP). Accounting data is downloaded from the merged CRSP/Compustat North America Fundamental Annual and the Fundamental Quarterly Database (Wharton Research Data Services, 2018).

We use all available common stocks on the merged CRSP/Compustat North America data, and include all stocks that are listed on either NYSE, AMEX or NASDAQ. After introducing these requirements, the dataset contains 199 127 observations. We do not remove financial firms, as there are no indications of Asness et al. doing so in the original paper.

For the CRSP monthly dataset we introduce the same requirements as for the merged CRSP/Compustat dataset. We use all available common stocks that are listed on either NYSE, AMEX or NASDAQ. Also, if a stock lacks ordinary return data while delisting return is available, we use the delisting return. Asness et al. set delisting returns at minus 30% if the delisting is performance related and delisting return is missing. Each delisting in the CRSP dataset has a code that classifies whether the delisting is performance related or not (Shumway, 1997). However, we do not find any performance related delistings where delisting return data is missing. Stocks that lack return data are deleted, resulting in a dataset of 3 162 085 observations. We align accounting variables at the end of the firm's fiscal year ending anywhere in calendar year t-1 to June of calendar year t following the standard convention of Fama and French (1992).

Factor returns for the market, value, size, momentum, profitability and investments factors are downloaded from Kenneth French's data library (French, 2018). The first observation in the dataset that contains return data for all six factors is from July 1963, which makes July 1963 a natural starting point for the sample.

Further, QMJ is a composite quality measure, and consist of 16 individual quality measures. These 16 measures again consist of six profitability measures, five growth measures and five safety measures. Profitability is measured as gross profits over asset (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR) and accruals (ACC). Growth is measured as 5-year growth in the profitability measures, excluding accruals. Safety is measured by beta (BAB), leverage (LEV), bankruptcy risk in terms of Altman's Z-score (Z-score) and Ohlson's O-score (O-score), and earnings volatility (EVOL). After computing these measures and merging the annual accounting data with the CRSP monthly return data, we have 1 346 395 observations in the merged monthly dataset. See the appendix for the full list of all the variables downloaded and formulas for the quality measures.

It is a challenge to calculate the quality measures in the exact same manner as in the original paper. We are forced to make assumptions on how to compute the measures in terms of which variables we allow to be missing and which observations we remove from the sample due to missing observations. We do not know if we make the same assumptions as Asness et al., which can potentially affect our replication results. This is discussed in the next section.

3.1.2 Data Cleaning

Having described our data sources, we proceed with a thorough explanation of our data cleaning process. In this section we only comment the quality measures that requires us to make assumptions as to how Asness et al. have conducted their computations. If a quality measure is not mentioned in this section, we use the same methodology as in the original paper. Formulas for every quality measure and input variables can be found in the appendix.

We begin the data cleaning process with working capital, which is an input variable in CFOA, ACC, growth in CFOA and Altman Z-score. We allow income taxes payable to be missing within working capital to avoid losing too many observations. This is not problematic, as income taxes payable often is a very small number in the merged CRSP/Compustat dataset. Moreover, in our GPOA and GMAR calculation we allow cost of goods sold to be missing, and missing revenues are imputed with sales. We also allow depreciation to be missing in CFOA and ACC, as depreciation is systematically missing in the merged CRSP/Compustat dataset the first years after a company is registered.

The growth ratios are the 5-year growth in profitability ratios excluding ACC, and therefore the assumptions made for the profitability ratios apply to the growth ratios. Moreover, as we use 5-year growth, companies who have yet to reach their fifth year in the merged CRSP/Compustat dataset will not have growth measures. Consequently, to be included in return tests we require companies to have at least five years of Compustat data.

To compute LEV, we allow minority interest and preferred stock to be missing. We do not consider this problematic, considering both variables tend to be zero for the companies where minority interest and preferred stock are reported. For the O-score, we use the market equity from the end of the previous month, and do not allow any variables to be missing. O-score also require CPI as input. To avoid forward-looking bias, we use the previous year's annual CPI, downloaded from the US Bureau of Labour Statistics (2018). For Altman's Z-score, we allow working capital and retained earnings to be missing.

To estimate EVOL, we use standard deviation of quarterly ROE and require 12 non-missing quarters. If only annual data is available, we use standard deviation of annual ROE and require five non-missing fiscal years. To merge quarterly ROE data with the monthly stock data, we align the quarterly data to fiscal quarters in the monthly dataset using fiscal year end. For example, if the fiscal year end for a firm is January then fiscal quarter one will be February, March and April. Then, we proceed to merge the monthly stock data and the quarterly ROE data on fiscal year and fiscal quarter. Quarterly standard deviations are annualized to be compatible with the annual standard deviations.

For our BAB estimates, the following equation describes the monthly estimate for the beta of stock i:

$$\beta_i = \frac{\sigma_i}{\sigma_m}\rho \tag{1}$$

σ_i and σ_m are the estimates for standard deviation for stock i and the market, and ρ is their correlation. We use daily returns to estimate volatilities of the individual stocks, volatility of the market, and the correlation between each individual stock and the market. Also, we use a one-year rolling standard deviation for individual stock and market volatility and a rolling five-year correlation of stock i and the market. For the volatilities we require at least six months (120 trading days) of non-missing data, and for the correlations we require at least three years (750 trading days) of non-missing data. See Frazzini and Pedersen (2014) for more details.

3.1.3 Quality Score

To obtain a composite quality score for each stock, we proceed to rank each stock cross-sectionally on each individual quality measure x every month. All quality measures are ranked in ascending order, except BAB and EVOL, which are ranked in descending order:

$$r_x = rank(x) \tag{2}$$

Next, we calculate z-scores by rescaling the ranks, such that the cross-sectional mean is zero and the cross-sectional standard deviation is one for every quality measure x each month:

$$z(x) = z_x = \frac{[r_x - \bar{r}_x]}{\sigma(r_x)} \tag{3}$$

We compute the profitability z-score by averaging z-scores of gross profits over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR) and accruals (ACC).

$$Profitability = z\left(z_{gpoa} + z_{roe} + z_{roa} + z_{cfoa} + z_{gmar} + z_{acc}\right) \tag{4}$$

We compute the growth z-score by averaging the z-scores of 5-year growth in gross profits over assets (ΔGPOA), return on equity (ΔROE), return on assets (ΔROA), cash flow over assets (ΔCFOA) and gross margin (ΔGMAR). Δ denotes 5-year growth.

$$Growth = z\left(z_{\Delta gpoa} + z_{\Delta roe} + z_{\Delta roa} + z_{\Delta cfoa} + z_{\Delta gmar}\right) \tag{5}$$

We compute the safety z-score by averaging the z-score of beta (BAB), leverage (LEV), Ohlson's O-score (O-score), Altman's Z-score (Z-score) and earnings volatility (EVOL) and for each stock in each month.

$$Safety = z(z_{bab} + z_{lev} + z_{o-score} + z_{z-score} + z_{evol}) \tag{6}$$

To calculate the total quality score, we take the average of the profitability, growth and safety z-score.

$$Quality = z(Profitability + Safety + Growth) \tag{7}$$

If measures within profitability, safety or growth scores are missing, we simply average the remaining measures to obtain the profitability, safety or growth score. For example, if the GPOA z-score is missing, we take the average of the z-score of the other profitability measures to obtain the profitability z-score. This means, if a stock only has available data for one out of 16 quality measures, it will have a profitability, growth or safety score. On the other hand, we require a stock to have a profitability score, a growth score *and* a safety score to be assigned a quality score. It is unclear whether this particular approach differs from the original paper.

3.2 Portfolio Formation

In this section we present the results of our replication of the QMJ strategy. First, we replicate quality-sorted portfolios. Next, we replicate the QMJ factor and test for abnormal returns using a selection of asset pricing models. This is done to prove that we are capable of implementing the methodology of Asness et al., as we create QMJ strategies with modifications later in this thesis.

3.2.1 Quality-Sorted Portfolios

To construct quality-sorted portfolios, we sort all stocks on their respective quality score each month. Then, we use NYSE quality breakpoints to sort stocks into ten quality portfolios. Portfolios are value-weighted using market equity from the last trading day of the previous month.

In Table 1, we present ten quality-sorted portfolios and a long-short strategy that is long the highest quality portfolio and short the lowest quality portfolio. Panel A shows our replication, while panel B shows the results of Asness et al. The original results can also be found in Table 4 in the original paper. We provide excess returns and alphas with respect to the CAPM, 3-factor and 4-factor model.

For the CAPM we use the first right-hand side variable, for the 3-factor model we use the three first right-hand side variables, and for the 4-factor model we use all right-hand side variables of Equation 8:

$$r_t^e = \alpha + \beta^{MKT} MKT_t + s^{SMB} SMB_t + h^{HML} HML_t + u^{UMD} UMD_t + \varepsilon_t \tag{8}$$

In the original paper, the authors claim excess returns rise monotonically with quality. As Panel B shows, this is not obvious. Still, there are extreme values in the bottom and top decile, which is valuable for the long-short strategy. In Panel A we see similar results for quality sorted excess returns as reported in Panel B. In Panel A, excess return varies between 0.51% to 0.59% from decile two till decile nine, and decile ten has by far the highest excess return with 0.69%. This is almost identical to the original paper. However, we are not able to assign the worst performing stocks to decile one as effectively as in the original paper. We find excess return of 0.46% per month for decile one, while Asness et al. find 0.29%. Given the degrees of freedom related to the calculation of the 16 quality measures, we find our results to be satisfying.

Moreover, the alphas presented in Panel A are similar to the original paper for all factor models reported. This indicates that the replication of the ten quality-sorted portfolios is successful.

3.2.2 The Quality Minus Junk Factor

After replicating the quality-sorted portfolios, we proceed with the replication of the QMJ factor. To construct QMJ, we sort stocks conditionally on size and then on quality. Each month, stocks are sorted into two size portfolios, with the median NYSE market equity as the size breakpoint. Next, both small and big stocks are sorted into three quality portfolios based on their total quality score by a 30/40/30 split. The lowest quality portfolios are characterized as junk and the highest quality portfolios are characterized as quality. These six portfolios are refreshed and rebalanced every calendar month to maintain value weights. The QMJ factor returns are the monthly average return of the small high-quality and big high-quality portfolios, minus the small junk and big junk portfolios (Equation 9). We follow the same procedure to construct factor portfolios for profitability, growth and safety.

$$QMJ = 0.5\ (Small\ Quality - Small\ Junk) + 0.5\ (Big\ quality - Big\ Junk) \tag{9}$$

Table 1

Quality-Sorted Portfolios

This table shows the calendar-time portfolio returns of the ten quality sorted portfolios for the sample period from July 1963 to December 2016. Panel A shows our replication, while Panel B shows the results of Asness et al. (2017). Each month, stocks are ranked on the composite quality score consisting of 16 individual quality measures, and they are sorted into ten portfolios based on breakpoints from NYSE stocks. Portfolios are value-weighted and rebalanced every month based on the market capitalization from the previous month to maintain the value weight. The alphas reported for every decile is the intercept in the time-series regression for monthly excess returns. The excess returns are over the U.S. monthly T-bill rate. The explanatory variables in the time-series are the returns of the market, size (SMB), book-to-market (HML) and momentum (UMD). The alphas and the excess returns are reported in monthly percent, and the t-statistics are presented under the coefficient estimates in parentheses. Beta is the beta estimate from CAPM. Sharpe ratios are annualized. Significant excess returns and alphas at the 5% level are reported in bold.

Panel A: Replication results	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Excess Return	0.46	**0.51**	**0.55**	**0.59**	**0.54**	**0.53**	**0.57**	**0.55**	**0.59**	**0.69**	0.22
	[1.92]	[2.48]	[3.10]	[3.38]	[3.18]	[3.17]	[3.44]	[3.37]	[3.67]	[3.99]	[1.30]
CAPM alpha	-0.22	-0.08	0.03	0.08	0.03	**0.04**	0.08	0.06	0.11	**0.18**	**0.40**
	[-1.88]	[-0.84]	[0.37]	[1.04]	[0.51]	[0.53]	[1.17]	[0.96]	[1.77]	[2.50]	[2.43]
3-factor alpha	**-0.51**	**-0.35**	**-0.14**	-0.07	-0.07	-0.05	0.03	0.03	**0.14**	**0.38**	**0.88**
	[-5.24]	[-5.35]	[-2.19]	[-1.13]	[-1.07]	[-0.75]	[0.49]	[0.59]	[2.59]	[6.33]	[7.00]
4-factor alpha	**-0.34**	**-0.21**	-0.09	0.01	-0.06	-0.05	0.07	-0.01	**0.13**	**0.35**	**0.69**
	[-3.55]	[-2.69]	[-0.40]	[0.08]	[-1.03]	[-0.79]	[1.13]	[-0.18]	[2.11]	[5.75]	[5.49]
Beta	1.29	1.13	0.99	0.97	0.96	0.94	0.93	0.94	0.91	0.96	-0.33
Sharpe Ratio	0.26	0.33	0.41	0.45	0.43	0.42	0.46	0.45	0.49	0.54	0.17

Panel B: Original results	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Excess Return	0.29	**0.47**	**0.50**	**0.47**	**0.56**	**0.49**	**0.56**	**0.57**	**0.49**	**0.69**	**0.40**
	[1.16]	[2.31]	[2.65]	[2.70]	[3.35]	[2.87]	[3.36]	[3.42]	[2.97]	[4.01]	[2.43]
CAPM alpha	**-0.41**	-0.12	-0.05	-0.05	0.07	-0.02	0.06	0.07	0.00	**0.19**	**0.60**
	[-3.48]	[-1.65]	[-0.80]	[-0.80]	[1.17]	[-0.31]	[1.20]	[1.41]	[-0.08]	[2.86]	[3.98]
3-factor alpha	**-0.53**	**-0.23**	**-0.14**	**-0.12**	0.00	-0.07	0.03	0.06	0.03	**0.30**	**0.84**
	[5.82]	[-3.69]	[-2.36]	[2.27]	[-0.08]	[-1.32]	[0.64]	[1.24]	[0.60]	[5.62]	[7.44]
4-factor alpha	**-0.57**	**-0.35**	**-0.25**	**-0.22**	**-0.12**	-0.11	-0.02	0.06	0.04	**0.47**	**1.04**
	[-5.81]	[-5.41]	[-3.94]	[-4.13]	[-2.06]	[-1.94]	[-0.36]	[1.07]	[0.93]	[8.66]	[8.83]
Beta	1.27	1.15	1.09	1.04	1.01	1.02	1.00	0.98	0.95	0.93	-0.34
Sharpe Ratio	0.15	0.30	0.34	0.35	0.43	0.37	0.44	0.44	0.38	0.52	0.31

Return tests for the QMJ, profitability, safety and growth factors are presented in Table 2. We run regressions on the factor returns utilizing 3-factor, 4-factor, 5-factor and 6-factor asset pricing models. The 5-factor model contains the first five right-hand side variables, while the 6-factor model contains all right-hand side variables of Equation 10.

$$r^{e}_{QMJ,t} = \alpha + \beta^{MKT} MKT_t + s^{SMB} SMB_t + h^{HML} HML_t + w^{RMW} RMW_t + c^{CMA} CMA_t + u^{UMD} UMD_t + \varepsilon_t \quad (10)$$

In Table 2, we see indications of a successful replication of QMJ. Panel A shows the results of our factor regressions, while Panel B shows the results of Asness et al. The original results can also be found in Table 6 and Table 7 of the original paper. All the sub-components of QMJ and the QMJ factor deliver a statistically significant alpha in all the asset pricing models. The alphas are of approximately the same magnitude as in the original paper, with similar t-statistics. The monthly 6-factor alpha for QMJ is 0.22% compared to 0.30% in the original paper.

Moreover, we document similar factor loadings as in the original paper for all quality factor strategies. The replicated QMJ strategy is betting on low beta, big, low book-to-market, profitable, aggressive and outperforming stocks. However, we find some systematic deviations in factor loadings, which might help explain the lower QMJ alpha and excess returns. We systematically pick stocks that loads significantly positive on momentum for all quality factors, which differs from the results of Asness et al. They also find significant loadings on momentum for QMJ and safety, but they find insignificant loadings on momentum for profitability and growth. Quality strategies loading on momentum is not surprising, since high quality stocks tend to have offered high returns in the past.

The safety factor exhibits the largest deviations from the original paper in terms of excess returns and alphas. We document monthly excess returns of 0.02% and an average monthly 6-factor alpha of 0.17% compared to 0.22% and 0.30% respectively in the original paper. Furthermore, the factor loadings in the 6-factor model suggest that the replicated safety factor invests more in low book-to-market and less profitable stocks. The deviations in QMJ excess returns and alphas from the original paper can be attributed to the safety factor not yielding excess return and alphas of satisfactory magnitude in our replication.

There are several potential explanations for the deviations of the safety factor, as there are many degrees of freedom related the construction of the safety portfolios. For example, deviations can occur due to different assumptions in the data cleaning process or for the individual safety measures.

First, the authors of the original paper are vague and at times wrong in their explanations of the safety measures. They write that a stock with low Altman's Z-score is safe, while in fact a low Altman's Z-score is an indication of high bankruptcy risk (Altman, 1968). Since "Quality Minus Junk" is a working paper, we cannot exclude the possibility of imprecise documentation.

Second, deviations in the merge of accounting and return data can have an important impact on the results. Asness et al. does not provide any explanation on how they merge quarterly EVOL data with monthly returns data, or how they align beta estimates every month. We use a conservative merge to avoid forward-looking bias. If there are systematic differences in merging procedures, this could explain the deviations we observe for the safety factor.

Moreover, we find that the replicated factor strategies in Table 2 loads less on profitability, and more negatively on HML compared to the original paper. The negative value exposures are expected since the value factor HML is long cheap stocks. On the other hand, high-quality stocks are more expensive. The low profitability loadings might also be explained by the negative value exposure, as growth stocks tend to be less profitable than value stocks.

At last, we observe a Sharpe ratio of 0.18 for QMJ, which is quite low. We are not able to replicate the excess returns of the safety factor, and this translates into lower excess returns for the composite QMJ factor. Therefore, we find lower Sharpe ratios for the QMJ as volatility is not reduced proportionally. This results in low Sharpe ratios for all strategies that are based on the replicated QMJ strategy later in this thesis.

Nevertheless, the QMJ, profitability, safety and growth factors still deliver significant positive alphas controlling for 5- and 6-factor models. In addition, we infer based on the factor loadings that the replicated strategies invest in the same type of stocks as the original strategies. Thus, we deem the replication successful.

Table 2
Quality Minus Junk – Returns

This table shows the calendar-time portfolio returns and factor loadings of the QMJ, profitability, safety and growth portfolios. Panel A shows our replication, while Panel B shows the results of Asness et al. (2017). The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality. At the end of each calendar month all stocks in our U.S. sample from July 1963 to December are sorted on size based on their market capitalization. The size breakpoint is constructed using the median NYSE market equity. After sorting on size, the portfolios are sorted on quality, sorting both small cap stocks and large cap stocks on quality. Portfolios are value-weighted and rebalanced every month based on the market capitalization from the previous month to maintain the value weights. The QMJ factor return is the average return on the two high quality portfolios minus the average return on the low quality (junk) portfolios. The portfolio returns of profitability, growth and safety are constructed in a similar manner. The explanatory variables in the time-series are the returns of the market (MKT), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), and momentum (UMD) portfolios from Ken French's data library. Alpha is the intercept in the time-series regression. The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported in monthly percent, and the t-statistics are presented under the coefficient estimates in parentheses. Sharpe ratios are annualized. Significant excess returns and alphas at the 5% level are reported in bold.

	Panel A: Replication results				Panel B: Original results			
	QMJ	Profitability	Safety	Growth	QMJ	Profitability	Safety	Growth
Excess returns	0.12	**0.23**	0.02	0.08	**0.26**	**0.29**	**0.22**	0.07
	[1.33]	[2.91]	[0.17]	[0.86]	[3.01]	[3.92]	[2.26]	[0.88]
3-factor alpha	**0.46**	**0.50**	**0.38**	**0.28**	**0.46**	**0.40**	**0.53**	**0.16**
	[6.97]	[7.96]	[5.29]	[4.37]	[7.81]	[6.93]	[9.18]	[2.78]
4-factor alpha	**0.34**	**0.42**	**0.25**	**0.23**	**0.57**	**0.50**	**0.53**	**0.37**
	[5.28]	[6.67]	[3.58]	[3.55]	[9.22]	[8.32]	[8.69]	[6.32]
5-factor alpha	**0.37**	**0.43**	**0.25**	**0.31**	**0.34**	**0.29**	**0.41**	**0.19**
	[5.44]	[6.73]	[3.54]	[5.11]	[7.21]	[6.76]	[6.26]	[4.36]
6-factor alpha	**0.22**	**0.28**	**0.17**	**0.19**	**0.30**	**0.28**	**0.31**	**0.17**
	[3.71]	[5.17]	[2.50]	[3.53]	[6.39]	[6.46]	[5.02]	[3.98]
MKT	-0.15	-0.10	-0.32	0.01	-0.15	-0.08	-0.28	0.00
	[-10.25]	[-7.57]	[-18.70]	[0.66]	[-13.38]	[-7.28]	[-18.21]	[0.05]
SMB	-0.08	-0.07	-0.19	0.04	-0.09	-0.07	-0.18	0.05
	[-3.85]	[-3.70]	[-8.05]	[1.95]	[-5.72]	[-4.52]	[-8.51]	[3.42]
HML	-0.40	-0.42	-0.32	-0.35	-0.26	-0.29	-0.20	-0.24
	[-14.05]	[-15.96]	[-9.58]	[-13.27]	[-11.29]	[-13.98]	[-6.64]	[11.32]
CMA	-0.11	0.09	0.07	-0.38	-0.07	0.10	0.03	-0.44
	[-2.69]	[2.26]	[1.56]	[-9.79]	[-2.28]	[3.18]	[0.61]	[-14.54]
RMW	0.42	0.40	0.22	0.32	0.59	0.58	0.32	0.39
	[14.99]	[15.54]	[6.58]	[12.25]	[26.84]	[28.46]	[10.83]	[19.11]
UMD	0.11	0.07	0.14	0.05	0.05	0.01	0.13	0.02
	[8.33]	[5.80]	[8.57]	[4.25]	[4.91]	[1.18]	[8.95]	[1.95]
Sharpe Ratio	0.18	0.40	0.02	0.12	0.41	0.54	0.31	0.12

4. Sector Quality Effects within the QMJ

In this chapter, we present our first contribution to the work on QMJ by Asness et al. As established, a strategy that is long quality stocks and short junk stocks yields positive significant abnormal returns. For the rest of this thesis, we pursue a risk-based explanation for these abnormal returns. We investigate whether sector quality effects are the driver of QMJ abnormal returns. If the strategy is aggressively invested in certain sectors, it is exposed for risk not captured by asset pricing models. Within a sector, stocks tend to be exposed to the same types of risk. Thus, by investing heavily in a few sectors, the diversification of the strategy is reduced.

For the analysis of sector quality effects within QMJ, we impose new data requirements for the sample in addition to those described in Section 3.1. We use the Global Industrial Classification Standard (GIC) to classify stocks into eleven sectors, and therefore we use all available common stocks that have a GIC code in the merged CRSP/Compustat North America dataset. We require sectors to have at least ten observations every month. Real estate (GIC code 60) is excluded due to few observations, which results in a total of ten sectors in the sample. After introducing the new requirements, the dataset contains 1 226 284 observations.

Asness et al. (2000) claim a wide industry definition might hide the importance of differences from industry means and suggest assigning stocks to 48 industries instead. In Chapter 6, we conduct an analysis for a 48-industry sort as a robustness test for the sector sort.

4.1 Within Sector Test: Portfolios within the Individual Sectors

As a first test for sector quality effects in the QMJ strategy, we follow the methodology of Moskowitz and Grinblatt (1999) to compute QMJ factor returns within each sector. We proceed to sort stocks conditionally, first on size and then on quality within each sector. The size breakpoint is the median NYSE market equity of each sector. After sorting on size, the portfolios are sorted on quality within each sector. Each size portfolio is split into three quality portfolios, by assigning stocks to the bottom 30% (junk), middle 40% and top 30% (quality). Portfolios are value-weighted and rebalanced every month based on the market capitalization of each sector from the last trading day of the previous month to maintain the value weights.

The QMJ factor return is the average return on the two high quality portfolios minus the average return on the low quality (junk) portfolios in each sector s:

$$QMJ_s = 0.5\ (Small\ Quality_s - Small\ Junk_s) + 0.5\ (Big\ quality_s - Big\ Junk_s) \qquad (11)$$

The test is simple; if sector quality effects drive the abnormal returns of QMJ, the QMJ factor returns within each sector should not yield positive significant alphas. If so, the test indicates that the QMJ bets on sector outperformance, as it is not consistently long the quality stocks and short the junk stocks in each sector throughout the sample. In other words, the QMJ invests sporadically in sectors, which implies lack of diversification within the QMJ.

Table 3 presents alphas of the QMJ strategy within each sector. QMJ earns positive significant alphas in five out of ten sectors in the 5-factor model, and in two out of ten sectors in the 6-factor model. Note that QMJ for the entire sample earns a monthly 6-factor alpha of 0.22%, with a t-stat above 3. For such a strong strategy to only deliver significant 6-factor alphas in two out of ten sectors is a sign of sector quality effects within the QMJ strategy. None of the within-sector alphas are above the t-statistic hurdle of 3 proposed by Harvey et al. (2015).

Since QMJ is a composite quality measure where stocks are ranked on 16 individual quality measures, the sector differences found in Table 3 are hard to intuitively explain. Over time, we expect to see systematic differences between sectors, for example in terms of capital structure or cost structure. For individual quality measures, we expect these differences to be easier to measure. However, interpretations are rather unclear when averaging 16 individual quality measures. We cannot explain with certainty why a sector exhibits a quality trend within the QMJ framework.

Furthermore, as QMJ is based on 16 individual quality measures, the sector dependency within the strategy should be reduced. The composite measure captures several quality aspects of a stock, and it is reasonable to believe sector differences will be reduced compared to an individual measure. As seen in Table 3, the lack of significant alphas suggests the averaging of quality measures is not enough to reduce sector dependency entirely within the QMJ strategy.

Table 3
Quality Minus Junk Within Sectors

This table shows average monthly alphas for the QMJ strategy within each sector from July 1963 through December 2016. The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality within each GIC sector. The size breakpoint is constructed using the median NYSE market equity of each sector. After sorting on size, the portfolios are sorted on quality, sorting both small cap stocks and large cap stocks on quality. Portfolios are value-weighted and rebalanced every month based on the lagged market capitalization within each GIC sector to maintain the value weights. The QMJ factor return is the average return on the two high quality portfolios minus the average return on the two low quality (junk) portfolios within each sector. Alpha is the intercept in the time-series regression and is reported in monthly percent. T-statistics are presented under the estimates in parentheses. The data for the explanatory variables is downloaded from the Ken French's data library. Significant alphas at the 5% level are reported in bold.

	Energy	Materials	Industrials	Consm.disc	Consum.stpl	Health	Financials	IT	Telecom	Utilities
3-factor alpha	**0.59**	**0.35**	**0.25**	**0.48**	**0.37**	**0.33**	**0.38**	0.23	0.28	0.14
	[3.55]	[2.58]	[2.45]	[3.60]	[3.05]	[2.05]	[2.53]	[1.43]	[0.88]	[1.66]
4-factor alpha	**0.48**	**0.17**	**0.23**	**0.31**	**0.28**	0.31	0.26	0.13	0.13	0.07
	[2.87]	[1.25]	[2.15]	[2.32]	[2.30]	[1.88]	[1.70]	[0.79]	[0.42]	[0.88]
5-factor alpha	**0.48**	**0.29**	0.10	**0.36**	**0.32**	0.05	**0.32**	0.17	-0.19	0.09
	[2.86]	[2.07]	[1.00]	[2.66]	[2.59]	[0.36]	[2.11]	[1.04]	[-0.62]	[1.13]
6-factor alpha	**0.40**	0.14	0.10	0.23	**0.25**	0.07	0.23	0.09	-0.25	0.05
	[2.37]	[1.02]	[0.94]	[1.71]	[2.01]	[0.44]	[1.47]	[0.54]	[-0.81]	[0.56]

4.2 Demean Test: QMJ Demeaned by Average Sector Quality

We proceed to test the performance of the QMJ strategy after demeaning by average sector quality. Every month, we demean the quality score of each stock by subtracting the monthly average total quality score in each sector. Then, we employ the same portfolio sorts as in Section 3.2.2 to create a demeaned QMJ factor. If sector quality effects drive QMJ abnormal returns, the sector demeaning procedure should reduce the abnormal and excess returns of the strategy.

The demeaned QMJ abnormal returns and factor loadings are reported in Table 4. Demeaning each stock by the monthly sector quality average has a negligible effect on alphas and excess returns in the selection of factor models. Contrary to the *within-sector* test, this indicates sector quality effects do not have an impact on the alphas, excess returns or volatility of the QMJ strategy.

Table 4

QMJ Demeaned by Average Monthly Sector Quality Score

This table reports the calendar-time portfolio returns and factor loadings of the QMJ and demeaned QMJ portfolios from July 1963 through December 2016. The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality. At the end of each calendar month all stocks in our U.S. sample are sorted on size based on their market capitalization. The size breakpoint is constructed using the median NYSE market equity. After the portfolios are sorted on size the portfolios are sorted on quality. Portfolios are value-weighted and rebalanced every month based on the market capitalization to maintain the value weights. The QMJ factor return is the average return on the two high quality portfolios minus the average return on the low quality (junk) portfolios. The demeaned QMJ is constructed in a similar manner. We demean by subtracting the monthly average total quality score in each sector from each stock, before sorting stocks into portfolios on size and demeaned quality. The alphas are reported with respect to the CAPM and 3/4/5/6-factor models, and t-statistics are presented under the estimates in parentheses. The explanatory variables in the time-series are the returns of the market (MKT), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), and momentum (UMD) portfolios from Ken French's data library. The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported in monthly percent. Significant alphas and excess returns at the 5% level are reported in bold. Sharpe ratios are annualized.

	QMJ	Demeaned QMJ
Excess return	0.12	0.11
	[1.33]	[1.23]
3-factor alpha	**0.46**	**0.42**
	[6.97]	[6.60]
4-factor alpha	**0.34**	**0.33**
	[5.28]	[5.20]
5-factor alpha	**0.37**	**0.28**
	[5.44]	[4.94]
6-factor alpha	**0.22**	**0.22**
	[3.71]	[3.87]
MKT	-0.15	-0.19
	[-10.25]	[-13.83]
SMB	-0.08	-0.16
	[-3.85]	[-8.29]
HML	-0.40	-0.34
	[-14.05]	[-12.60]
CMA	-0.11	0.02
	[-2.69]	[0.47]
RMW	0.42	0.37
	[14.99]	[14.00]
MOM	0.11	0.09
	[8.33]	[6.79]
Sharpe ratio	0.18	0.17

4.3 Random Sector Test

To further assess potential sector quality effects in the QMJ factor, we construct random sector portfolios. We follow the methodology of Moskowitz and Grinblatt (1999) and replace every stock in sector s by another stock that has approximately the same quality score. We sort all stocks ascending on quality score each month, where every stock i is replaced by the stock with the second highest quality score compared to stock i, regardless of sector. This ensures that the quality characteristics of the random sector portfolios are the same as the original sector portfolios. If only sector quality effects are driving QMJ abnormal returns, we expect the new random sector portfolios to not exhibit alpha. The individual stock quality composition within the portfolios is the same, but the sector composition is reshuffled. By only changing sector composition, we can analyse whether sector quality effects are the only driver of QMJ abnormal returns. After assigning stocks to random sector portfolios, we follow the methodology described in Section 4.2 to create the QMJ returns within each random sector.

For momentum, Moskowitz and Grinblatt (1999) explain that the cross-sectional variation in the individual momentum component is much larger than the cross-sectional variation in the industry momentum component. Therefore, when a stock from one industry is replaced with another stock, the replacement stock is more likely to just have a very similar return to the original stock, than to be from the same industry. This also applies to the individual quality component and the sector quality component within QMJ.

Table 5 reports the random sector portfolio alphas. These portfolios earn significant abnormal returns in four out of ten random sectors in both the 5-factor and the 6-factor model. The number of sectors returning positive significant alphas is lower compared to the 5-factor test for the *within-sector* test from section 4.1. For the 6-factor model we observe the opposite; there are more significant alphas in the random sector portfolios compared to the *within-sector* test.

The result of the *random sector* test is inconclusive. First, there is a majority of sectors that does not exhibit significant alphas. The random sector portfolios will not exhibit alphas if *only* sector quality effects drive the abnormal returns. Therefore, this test is supportive evidence of sector quality effects not being the only driver of abnormal returns. Second, it is not given this test is suited for a sector sort. Moskowitz and Grinblatt find that the cross-sectional variation in individual momentum is much larger than the cross-sectional variation of industry momentum. Sectors will most likely exhibit larger cross-sectional variation than industries. In addition, after assigning stocks to random sector portfolios, 16.3% of the stocks are on average still within the same sector portfolio. Hence, the random sector portfolios may not be as random as perceived.

Table 5
Random Sector Portfolios

This table reports alphas for the QMJ random sector portfolios from July 1963 through December 2016. All stocks are sorted in ascending order on quality score each month. Every stock i is replaced by the stock with next highest quality score compared to stock i, regardless of sector. The QMJ factor is then constructed within each sector, at the intersection of six-value weighted portfolios formed on size and quality. The size breakpoint is constructed using the sector median NYSE market equity. After the portfolios are sorted on size the portfolios are sorted on quality within each GIC sector. Portfolios are value-weighted and rebalanced every month based on the lagged market capitalization of each sector to maintain the value weights. The QMJ factor return is the average return on the two high quality portfolios minus the average return on the two low quality (junk) portfolios. Alpha is the intercept in the time-series regression and is reported in monthly percent. T-statistics are presented under the estimates in parentheses. The data for the explanatory variables is downloaded from the Ken French's data library. Significant alphas at the 5% level are reported in bold.

	Energy	Materials	Industrials	Consm.disc	Consum.stpl	Health	Financials	IT	Telecom	Utilities
3-factor alpha	**0.47**	**0.65**	**0.57**	**0.61**	**0.24**	**0.47**	**0.33**	**0.64**	-0.17	0.10
	[2.65]	[4.28]	[5.31]	[5.38]	[1.55]	[2.70]	[2.07]	[4.55]	[-0.51]	[0.62]
4-factor alpha	0.34	**0.50**	**0.44**	**0.45**	0.16	0.28	0.16	**0.49**	-0.36	0.01
	[1.89]	[3.28]	[4.17]	[4.03]	[1.06]	[1.60]	[0.98]	[3.48]	[-1.04]	[0.09]
5-factor alpha	0.23	**0.52**	**0.45**	**0.44**	0.06	0.20	0.19	**0.51**	-0.39	-0.03
	[1.34]	[3.45]	[4.36]	[4.06]	[0.41]	[1.19]	[1.20]	[3.69]	[-1.12]	[-0.21]
6-factor alpha	0.15	**0.41**	**0.36**	**0.32**	0.02	0.07	0.06	**0.40**	-0.52	-0.09
	[0.85]	[2.70]	[3.49]	[3.04]	[0.13]	[0.40]	[0.39]	[2.88]	[-1.48]	[-0.58]

4.4 Long Junk – Short Quality Test

To continue, we create portfolios that are long junk stocks from the highest quality sectors, and short quality stocks from the lowest quality sectors. This allows us to directly assess individual stock quality. We perform this test using two different methods. First, we create QMJ strategies that are long big junk and small junk stocks in the quality sectors and short big quality and small quality stocks in the junk sectors. Second, we create strategies that are long the junk stocks of the quality sector and short the quality stocks of the junk sector, without conditionally sorting on size.

For the *long junk – short quality* QMJ method, we create two alternative strategies. Moskowitz and Grinblatt sort their sample into 20 industries and perform this test by buying the worst performing stocks of the three best performing industries and selling the best performing stocks of the three worst performing industries. As we sort stocks into ten sectors, we conduct the test for both the two highest and lowest quality sectors, and for the single highest and lowest quality sector. The portfolios are then value-weighted and rebalanced within each sector each month. These strategies are presented in column 2 and 3 in Table 6.

Interestingly, we find that junk stocks in the highest quality sector on average scores lower on quality than quality stocks in the lowest quality sector. In other words, on average this strategy buys stocks with lower quality score than the stocks it sells. Therefore, if individual stock quality drives QMJ returns, this strategy should produce significant negative alphas. We expect junk stocks to perform worse than quality stocks regardless of sector if there are no sector quality effects in play.

As presented in Table 6, alphas in column 2 and 3 are positive for both strategies in all factor models. We test whether the alphas are *negative*, and therefore use a one-tailed t-test with a t-stat threshold of 1.65. The QMJ strategy that is long junk in the two high-quality sectors, and short quality in the two low-quality sectors earns an alpha of 0.38% in the 6-factor model with a t-stat of 1.56. The QMJ strategy that is long junk in the sector scoring highest on quality, and short quality in the sector scoring lowest on quality earns a 5-factor alpha of 0.42% with a t-stat of 1.93. We expect junk stocks to be outperformed by quality stocks if individual stock quality drives QMJ abnormal returns. As we observe the opposite, this strongly suggests sector quality effects drive abnormal returns of the QMJ strategy.

We also examine the effect of going long junk stocks in the sectors with the highest quality score and short quality stocks from the sectors with the lowest quality score, without conditionally sorting on size. Based on this approach, we create two strategies. First, sectors are ranked each month on average quality score and stocks are sorted into ten quality deciles based on NYSE sector breakpoints. We proceed to create portfolios that are long the junk decile of the two sectors scoring highest on quality, and short the highest quality decile of the two sectors scoring lowest on quality each month. Second, we create a strategy where stocks are sorted into five quality quintiles instead of deciles. These strategies are presented in column 4 and 5 of Table 6. The long and short portfolio returns are value-weighted separately, and the portfolios are rebalanced every month.

Again, we find the average quality score of junk stocks in the high-quality sectors to be lower than the average quality score of the quality stocks in the low-quality sectors. The interpretation of this test is the same as for the *long junk – short quality* QMJ test above: If individual stock quality drives abnormal returns, we expect this portfolio to produce significantly negative abnormal returns. If only sector quality effects drive QMJ abnormal returns, we expect the opposite.

As column 4 and 5 in Table 6 demonstrate, we find positive alphas that are large in magnitude, with significant 5-factor alphas for both strategies. For this test to support individual quality being a driver of abnormal returns, we expect a negative and significant alpha. The positive alphas strongly suggest sector quality effects drive QMJ abnormal return.

Table 6
Long Junk - Short Quality

This table reports the 3-, 4-, 5- and 6-factor alphas of four strategies that are long junk stocks from high-quality sectors, and short quality stocks from low-quality sectors. The sample runs from July 1963 through December 2016. The strategies presented in column 2 and 3 follow the methodology of QMJ portfolio creation: At the end of each month, all stocks are sorted on size based on market capitalization within each sector. The size breakpoint is constructed using the median NYSE market equity for the sector. Then, stocks within the size portfolios are sorted on quality score. Strategy 1 (QMJ top 2/bottom 2), presented in the second column of this table, goes long big junk and small junk of the two highest quality industries, and short big quality and small quality of the two lowest quality industries. Strategy 2 (QMJ top/bottom), presented in the third column of this table, goes long small and big junk of the highest quality sector, and short small and big quality of the lowest quality sector. Portfolios are value-weighted and rebalanced every month based on the market capitalization from the previous month to maintain the value weights. The strategies presented in column 4 and 5 are sorted only on quality: At the end of each month, stocks are sorted into ten quality sorted portfolios within each sector, using NYSE breakpoints. Strategy 3 (Quality decile) is long the junk decile of the two highest quality sectors, and short the quality decile of the two lowest quality sectors. Strategy 4 (Quality quintile) is long the junk quintile of the two highest quality sectors, and short the quality quintile of the two lowest quality sectors. Portfolios are value-weighted and rebalanced every month based on the market capitalization from the previous month to maintain the value weights. The alphas reported for every strategy is the intercept in the time-series regression for monthly excess returns. The excess returns are over the U.S. monthly T-bill rate. The explanatory variables in the time-series are the returns of the market, size (SMB), book-to-market (HML), momentum (UMD), investments (CMA) and profitability (RMW). The alphas are reported in monthly percent. T-tests are one-tailed, and the t-statistics are presented under the coefficient estimates in parentheses. Significant alphas at the 5% level are reported in bold.

	QMJ top 2/bottom 2	QMJ top/bottom	Quality decile	Quality quintile
3-factor alpha	0.17	0.24	0.06	0.16
	[0.60]	[1.11]	[0.26]	[0.87]
4-factor alpha	0.10	0.13	0.09	0.14
	[0.35]	[0.60]	[0.37]	[0.71]
5-factor alpha	0.25	**0.42**	**0.40**	**0.36**
	[0.87]	[1.93]	[1.65]	[1.86]
6-factor alpha	0.38	0.31	0.38	0.31
	[1.56]	[1.40]	[1.56]	[1.59]

4.5 Sector Neutral QMJ

As a final test, we create QMJ strategies that are not allowed to invest aggressively in sectors – a sector neutral QMJ. We use two methods to restrict the QMJ strategy, a market value-weighted target sector weight and an equal-weighted 10% target sector weight. If these strategies deliver large and significant abnormal returns, we can disregard our hypothesis of sector quality effects within QMJ. On the other hand, if the constrained strategies fail to deliver abnormal returns, we have found further evidence of sector quality effects.

To begin, we calculate total market equity and market equity of each sector every month from the CRSP dataset. This allows us to compute value-weighted target sector weights. After we compute the value-weighted return of the six portfolios sorted conditionally on size and quality as presented in Section 3.2.2, we calculate the actual sector weight in the unrestricted QMJ strategy at the start of each month. We rescale the investment in each stock to the CRSP target weight, by creating a scaling factor for the value-weighted returns, as shown in Equation 12:

$$\frac{Target\ sector\ weight}{Actual\ sector\ weight} * Value\text{-}weighted\ return \tag{12}$$

The value-weighted returns are multiplied by the scaling factor, which ensures the sector weights of the sector neutral portfolios match the target sector weights. This means, if the QMJ sector weight is less than the target sector weight, the strategy increases its exposure to this sector. If the QMJ sector weight is greater than the target sector weight, the strategy reduces its exposure to this sector. To explore a more conservative sector restriction of the QMJ, we also create a QMJ strategy that is equally invested in each sector. This means we set the target sector weight to 10% for each sector in equation 12.

The results from the return tests on the sector neutral QMJ strategies are presented in Table 7. Panel A presents the strategy with value-weighted CRSP target sector weights, while Panel B presents the strategy with equal-weighted target sector weights of 10%. The factor loadings presented in Table 7 indicate that the sector neutral QMJ strategies invest in the same type of stocks as the unrestricted QMJ strategy. However, the 6-factor alphas are greatly reduced. In Panel A we report an insignificant 6-factor alpha of 0.09%, while in Panel B we report a barely significant 6-factor alpha of 0.13%. As documented, the unrestricted QMJ strategy yields a 6-factor alpha of 0.22%. These results are supportive of sector quality effects within QMJ, as the sector neutral strategies perform worse than the unrestricted QMJ in return tests.

To summarize this chapter, we find that the *within-sector* and *long junk – short quality* tests point towards sector quality effects in the QMJ. The *random sector* test is supportive of there not being only sector quality effects that drive abnormal returns, while the *demeaning* test suggests no sector quality effects in the QMJ. At last, the *sector neutral* QMJ strategies do not match the performance of the unrestricted QMJ. This adds to the evidence of sector quality effects being present in the QMJ. Therefore, we conclude that sector quality effects partially drive the abnormal returns of the QMJ strategy.

Table 7

Sector Neutral QMJ Portfolio Alphas

This table shows the calendar-time portfolio returns and factor loadings of the sector neutral QMJ portfolios from July 1963 through December 2016. Panel A shows a sector neutral strategy using CRSP value-weighted target sector weights, while Panel B shows the strategy using equal-weighted 10% target sector weights. The sector neutral portfolios are constructed at the intersection of six-value weighted portfolios formed on size and quality. At the end of each calendar month all stocks are sorted on size based on their market capitalization. The size breakpoint is constructed using the median NYSE market equity. After the portfolios are sorted on size the portfolios are sorted on quality, sorting both small cap stocks and large cap stocks on quality. Portfolios are value-weighted and rebalanced every month based on the market capitalization to maintain the value weights. Based on the target sector weights, value-weighted returns are rescaled such that the QMJ strategy sector weights matches the target weights. The sector neutral QMJ factor return is the average return on the two high quality portfolios minus the average return on the two low quality (junk) portfolios. The excess return (over the U.S. monthly T-bill rate) and alphas are reported with respect to the CAPM and 3/4/5/6-factor model, and t-statistics are presented under the estimates in parentheses. The explanatory variables in the time-series are the returns of the market (MKT), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), and momentum (UMD) portfolios from Ken French's data library. Alphas and the excess returns are reported in monthly percent. Sharpe ratios are annualized. Significant alphas and excess returns at the 5% level are reported in bold.

	Panel A: Value-weighted target sector weights				Panel B: Equal-weighted target sector weights			
	6-factor	5-factor	4-factor	3-factor	6-factor	5-factor	4-factor	3-factor
Excess return	0.04	0.04	0.04	0.04	0.01	0.01	0.01	0.01
	[0.51]	[0.51]	[0.51]	[0.51]	[0.11]	[0.11]	[0.11]	[0.11]
Alpha	0.09	**0.16**	**0.19**	**0.30**	**0.13**	**0.21**	**0.22**	**0.33**
	[1.53]	[2.48]	[2.96]	[4.52]	[1.96]	[3.12]	[3.16]	[4.65]
MKT	-0.16	-0.17	-0.18	-0.20	-0.25	-0.26	-0.27	-0.29
	[-11.34]	[-11.86]	[-11.80]	[-12.91]	[-15.46]	[-15.86]	[-16.12]	[-17.10]
SMB	-0.16	-0.15	-0.25	-0.24	-0.14	-0.14	-0.22	-0.22
	[-8.33]	[-7.63]	[-11.66]	[-11.04]	[-6.53]	[-5.98]	[-9.58]	[-9.11]
HML	-0.19	-0.25	-0.20	-0.24	-0.27	-0.33	-0.27	-0.31
	[-7.03]	[-9.00]	[-8.46]	[-10.10]	[-8.56]	[-10.47]	[-10.68]	[-12.23]
CMA	-0.03	0.01			-0.02	0.02		
	[-0.73]	[0.29]			[-0.46]	[0.46]		
RMW	0.37	0.39			0.33	0.35		
	[13.64]	[14.05]			[10.61]	[11.13]		
MOM	0.11		0.12		0.11		0.12	
	[7.84]		[8.04]		[7.16]		[7.57]	
Sharpe ratios	0.07	0.07	0.07	0.07	0.01	0.01	0.01	0.01

5. Volatility-Managed Sector Neutral QMJ

In Chapter 4 we establish a potential risk-based explanation for QMJ abnormal returns, as the strategy seems to invest aggressively in sectors that outperform rather than individual quality stocks. Consequently, the QMJ lacks diversification. We also show that a sector neutral QMJ strategy performs worse in return tests than the unrestricted QMJ.

However, we do not believe the quality puzzle is explained yet. Extensive research show that volatility-managed factor strategies exhibit increased excess returns and alphas, with reduced volatility. Barroso and Santa-Clara (2015) create a dynamic momentum strategy that is scaled by forecasted and preferred volatility, which doubles Sharpe ratio and greatly reduces crash risk. Moreira and Muir (2017) document large alphas and increase in Sharpe ratios for a selection of volatility-managed factors, such as value and profitability. If a volatility-managed version of the sector neutral QMJ strategy delivers significant positive abnormal returns, sector bets cannot explain the abnormal returns of the QMJ strategy. In this chapter we proceed with the sector neutral QMJ that use CRSP value-weighted target sector weights, as presented in Section 4.5. Results for the volatility-managed sector neutral QMJ which invests 10% in each sector are available upon request.

5.1 Portfolio Formation

To implement a volatility-managed sector neutral QMJ, we follow the methodology of Barroso and Santa-Clara (2015). They use daily strategy returns to forecast volatility, in order to volatility-manage the monthly strategy. To construct daily sector neutral QMJ portfolios, we follow the methodology provided in Section 4.5, but with daily stock returns. Each day, we sort stocks on size based on their market capitalization from the start of the month. The size breakpoint is constructed using the median NYSE market equity. Then, we sort the size portfolios on quality. The bottom 30% of observations are classified as junk stocks, while the top 30% of observations are classified as quality stocks. Daily returns are then value-weighted by the market equity from the last trading day of the previous month.

Next, the daily value-weighted returns are multiplied by the scaling factor presented in Section 4.5 (Equation 12), which ensures the daily sector weights of the portfolios match the target sector weights from the beginning of the month. The daily sector neutral QMJ return is the average return on the high-quality portfolios minus the average return on the low-quality (junk) portfolios.

To forecast sector neutral QMJ variance, we compute six-month realized variance of the daily returns at the end of each month. The realized variance is the sum of squared daily returns from the previous 126 days, which is averaged to daily variance. The daily realized variance is then multiplied with 21 to obtain a monthly variance forecast. See Equation 13 for the variance forecast, where day 126 is the last day of month t-1:

$$\hat{\sigma}^2_{QMJ,t} = \frac{21}{126}\sum_{j=1}^{126} r^2_{QMJ,j} \tag{13}$$

Barroso and Santa-Clara (2015) use a volatility target of 12% annualized standard deviation. We calculate volatility-managed strategy returns for volatility targets of 5%, 12% and 15% to show how the strategy is affected by different volatility targets.

To compute time-varying strategy weights, the annual standard deviation target is converted to monthly standard deviation. Then, the returns of the *monthly* sector neutral QMJ strategy is multiplied by the ratio of target volatility over forecasted volatility (equation 14). This scaling can be conducted without constraints, as the monthly sector neutral QMJ strategy is a self-financing, zero-investment strategy. For example, if the strategy weight is 2, it means we go two times into the strategy.

$$r_{QMJ^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_{QMJ,t}}\, r_{QMJ,t} \tag{14}$$

To assess the performance of the volatility-managed sector neutral QMJ, we present dynamic strategy weights, a number of return tests, descriptive statistics, and cumulative abnormal returns.

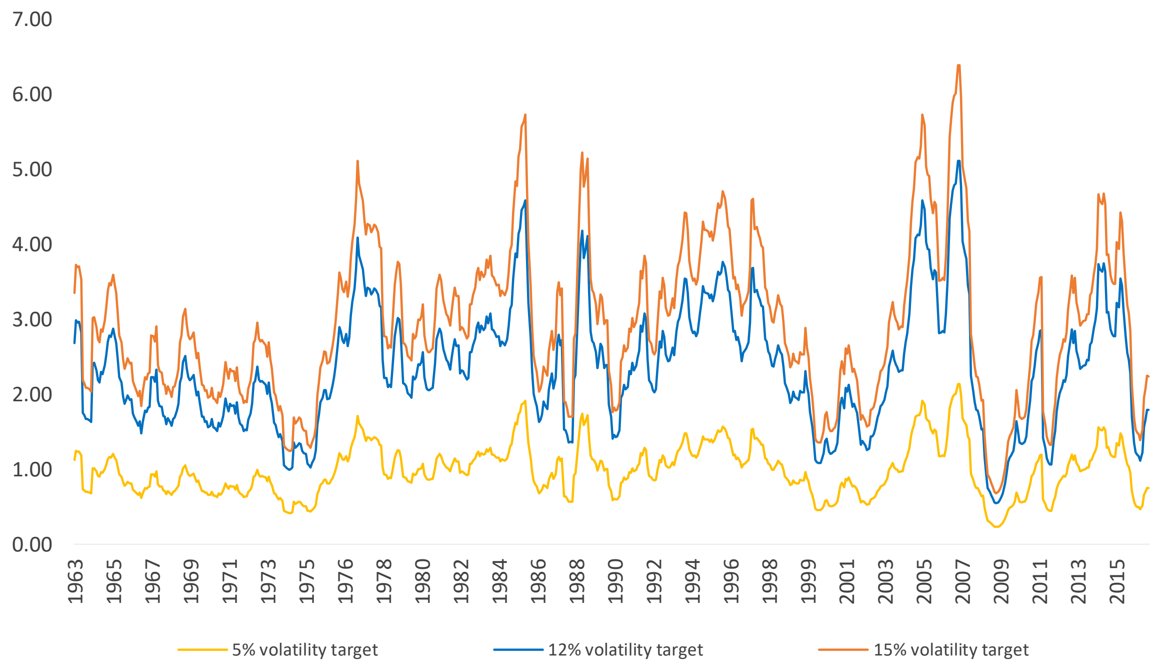
5.2 Results and Implications

In Figure 1 we present time-varying strategy weights ($\frac{\sigma_{target}}{\hat{\sigma}_{QMJ,t}}$) for the volatility-managed sector neutral QMJ strategies. Evidently, a higher volatility target translates to a higher exposure to the sector neutral QMJ. The average weights for the volatility-managed strategies are 0.98, 2.35 and 2.94 with volatility targets of 5%, 12% and 15% respectively. Barroso and Santa-

Clara (2015) document that the 12% volatility target of the momentum strategy results in an average strategy weight of 0.90. For QMJ, a 12% target results in average strategy weights of 2.35, indicating QMJ is a low volatility strategy compared to momentum. The 5% target might be a more sensible annual volatility target for QMJ, as the average weight is 0.98.

Figure 1
Strategy Weights

Figure 1 displays the time-varying strategy weights for the volatility-managed QMJ strategies with 5%, 12% and 15% volatility targets. The sample runs from July 1963 through December 2016. Weights are calculated as the ratio of monthly target standard deviation over the one-month standard deviation forecast, as shown in equation 14.



As presented in Table 8, the results from regressing the volatility-managed strategy returns on a 6-factor model are striking. The sector neutral QMJ fails to deliver significant positive alpha, while the volatility-managed versions deliver significant alphas above the t-statistic threshold of 3 proposed by Harvey et al. (2015). The most conservative strategy, with a volatility target of 5%, earns abnormal returns of 0.17% in the 6-factor model, with a t-statistic of 3.13. Thus, we are able to double the sector neutral QMJ strategy alpha. Both the 12%-version and the 15%-version yield higher alphas, but as we can infer from the identical t-statistics, this is followed by a proportional increase in volatility. Moreover, the factor loadings of the sector neutral QMJ strategy and the volatility-managed versions are similar to the factor loadings of the unrestricted QMJ. This means the strategies are picking the same type of stocks as the unrestricted QMJ strategy, without suffering from lack of diversification. The factor loadings of the volatility-managed versions seem to be scaled according to volatility target, a mechanical implication of the methodology of Barroso and Santa-Clara (2015).

From Table 8 we infer that the potential risk-based explanation for QMJ abnormal returns we present in Chapter 4 cannot explain the quality puzzle. As we can easily volatility-manage a sector neutral QMJ strategy, QMJ abnormal returns cannot be compensation for lack of diversification due to sector quality effects. Such a strategy is not difficult to implement and adds a new dimension to the quality puzzle.

In Table 9 we present descriptive statistics for the unrestricted QMJ, the sector neutral QMJ and the volatility-managed sector neutral QMJ strategies with volatility targets of 5% and 12% for the entire sample period. The table provides supporting arguments to how QMJ is improved by volatility-management while under sector restraints. First, Sharpe ratio is the same for volatility-managed QMJ and the unrestricted QMJ strategy regardless of volatility target. Second, maximum drawdown for the volatility-managed strategy with 5% volatility target is substantially lower than for the unrestricted QMJ strategy. By downscaling exposure to the sector neutral QMJ in times of volatility, crash risk appears to be reduced compared to the unrestricted QMJ strategy. Furthermore, the excess kurtosis drops from 4.14 for the sector neutral QMJ to 1.07 for the volatility-managed sector neutral QMJ, regardless of volatility target. The left skewness of the sector neutral QMJ improves to a right skewness. These results strongly indicate reduced crash risk for the volatility-managed strategies.

Table 9 also shows that the Sharpe ratios are equal for both volatility targets. The standard deviation of a high volatility target strategy is naturally higher than the standard deviation of a lower volatility target strategy, but is followed by proportionally higher excess returns. Therefore, the choice of volatility target is a question of investor preference. Investors with different risk-reward preferences might choose different volatility targets. This follows basic portfolio theory, where Sharpe ratio is maximized, before utility and risk aversion is introduced for portfolio optimization.

Table 8
Volatility-Managed Sector Neutral Quality Minus Junk

This table shows the calendar-time portfolio returns and factor loadings of the sector neutral QMJ portfolios and volatility-managed sector neutral QMJ portfolios. The sample runs from July 1963 through December 2016. The sector neutral portfolios are constructed at the intersection of six-value weighted portfolios formed on size and quality. At the end of each calendar month all stocks are sorted on size based on their market capitalization. The size breakpoint is constructed using the median NYSE market equity. After the portfolios are sorted on size the portfolios are sorted on quality, sorting both small cap stocks and large cap stocks on quality. Portfolios are value-weighted and rebalanced every month based on the market capitalization to maintain the value weights. The sector neutral strategy uses CRSP value-weighted target sector weights. Based on these target weights, value-weighted returns are rescaled such that the QMJ strategy sector weights matches the target weights. The sector neutral QMJ factor return is the average return on the two high quality portfolios minus the average return on the two low quality (junk) portfolios. In column 3, 4 and 5 we present three volatility-managed sector neutral strategies with annual volatility targets of 5%, 12% and 15% respectively. To volatility-manage the sector neutral strategy, the daily returns of the sector neutral QMJ are used to create a variance forecast to scale the strategy exposure depending on a volatility target and the volatility forecast for each month. Alphas are reported with respect to the CAPM and 3/4/5/6-factor models, and t-statistics are presented under the estimates in parentheses. The explanatory variables in the time-series are the returns of the market (MKT), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), and momentum (UMD) portfolios from Ken French's data library. The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported in monthly percent. Sharpe ratios are annualized. Significant alphas and excess returns at the 5% level are reported in bold.

	Sector neutral QMJ	Vol.managed 5%	Vol.managed 12%	Vol.managed 15%
Excess return	0.04	0.09	0.21	0.27
	[0.51]	[1.32]	[1.32]	[1.32]
3-factor alpha	**0.30**	**0.28**	**0.67**	**0.83**
	[4.52]	[4.89]	[4.89]	[4.89]
4-factor alpha	**0.19**	**0.23**	**0.55**	**0.69**
	[2.96]	[4.02]	[4.02]	[4.02]
5-factor alpha	**0.16**	**0.20**	**0.47**	**0.59**
	[2.48]	[3.74]	[3.74]	[3.74]
6-factor alpha	0.09	**0.17**	**0.40**	**0.50**
	[1.53]	[3.13]	[3.13]	[3.13]
MKT	-0.16	-0.13	-0.31	-0.39
	[-11.34]	[-9.92]	[-9.92]	[-9.92]
SMB	-0.16	-0.12	-0.30	-0.37
	[-8.33]	[-6.89]	[-6.89]	[-6.89]
HML	-0.19	-0.12	-0.29	-0.36
	[-7.03]	[-4.77]	[-4.77]	[-4.77]
CMA	-0.03	-0.09	-0.21	-0.26
	[-0.73]	[-2.39]	[-2.39]	[-2.39]
RMW	0.37	0.27	0.65	0.81
	[13.64]	[10.87]	[10.87]	[10.87]
MOM	0.11	0.04	0.10	0.13
	[7.84]	[3.48]	[3.48]	[3.48]
Sharpe ratios	0.07	0.18	0.18	0.18

Table 9

Descriptive Statistics

This table shows descriptive statistics for the unrestricted QMJ, sector neutral QMJ and volatility-managed sector neutral QMJ strategies with 5% and 12% volatility target. The sample runs from July 1963 through December 2016. Excess returns and standard deviations are in monthly percent. Sharpe ratios are annualized. Max drawdown is calculated as maximum loss from a peak during the sample.

Strategy	Period	Excess Return	Standard deviation	Sharpe ratio	Max drawdown	% Losing months	Worst monthly return	Kurtosis	Skewness
Unrestricted	1963-2016	0.12	2.32	0.18	-0.35	0.47	-0.14	3.44	-0.46
Neutral	1963-2016	0.04	2.11	0.07	-0.36	0.48	-0.13	4.14	-0.59
5% Scaled	1963-2016	0.09	1.71	0.18	-0.26	0.48	-0.06	1.07	0.11
12% Scaled	1963-2016	0.21	4.11	0.18	-0.53	0.48	-0.14	1.07	0.11

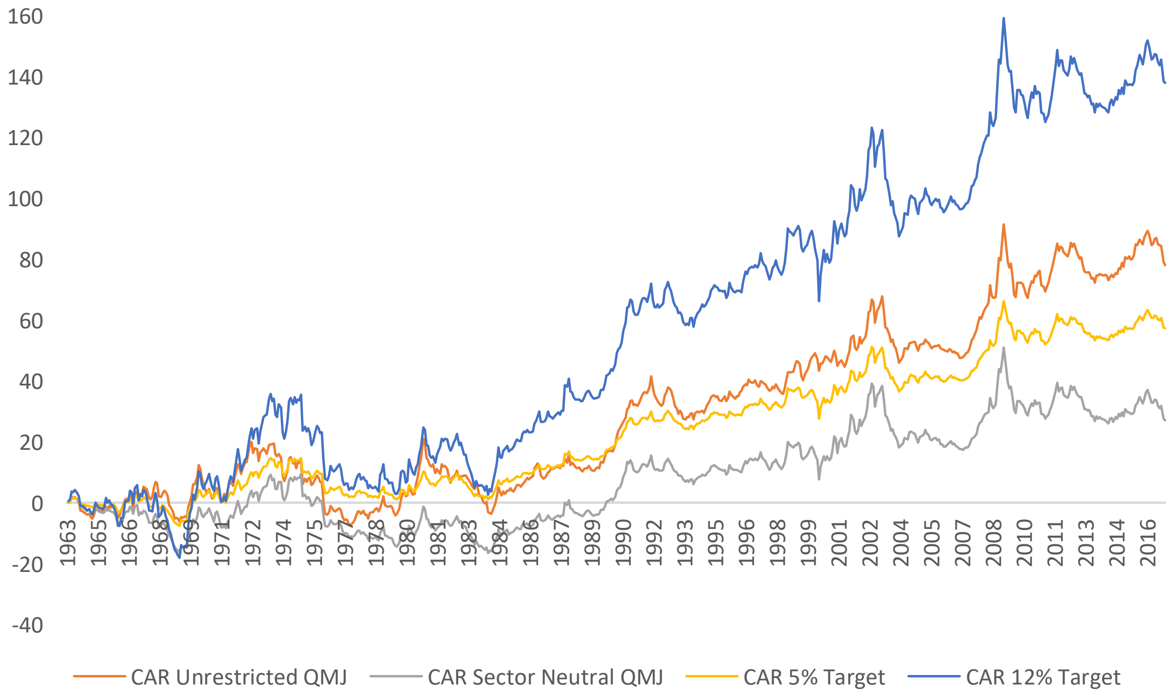
In figure 2 we plot the cumulative abnormal returns (CAR), which is the alpha plus the regression residuals, for the unrestricted QMJ, sector neutral QMJ and volatility-managed sector neutral QMJ strategies. The plot shows consistent risk-adjusted returns over time for the volatility-managed sector neutral strategies, indicating no particular subsample drives the abnormal returns. There are also improvements in sheer magnitude of risk-adjusted returns for the volatility-managed sector neutral QMJ compared to the sector neutral QMJ, regardless of volatility target.

In summary, we volatility-manage the sector neutral QMJ, and document significant improvements in strategy performance. With a 5% volatility target, the 6-factor alpha of the sector neutral QMJ doubles. Sharpe ratios are restored to the same level as for the unrestricted QMJ strategy, and crash risk is reduced. This result deepens the quality puzzle, as the sector quality effects within QMJ cannot explain QMJ abnormal returns.

Figure 2

Cumulative 6-factor Alpha

This figure shows a plot of the cumulative abnormal returns (alpha plus regression residual) for the unrestricted QMJ, sector neutral QMJ and volatility-managed sector neutral QMJ strategies (5%- and 12% target). The sample runs from July 1963 through December 2016. The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality. At the end of each calendar month all stocks are sorted on size based on their lagged market capitalization. The size breakpoint is constructed using the median NYSE market equity. After the portfolios are sorted on size the portfolios are sorted on quality, sorting both small cap stocks and large cap stocks on quality. Portfolios are value-weighted and rebalanced every month to maintain the value weights. The QMJ factor return is the average return on the two high quality portfolios minus the average return on the low quality (junk) portfolios. The sector neutral strategy uses CRSP value-weighted target sector weights. Based on these target weights, value-weighted returns are rescaled such that the QMJ strategy sector weights matches the target weights. The sector neutral QMJ factor return is the average return on the two high quality portfolios minus the average return on the two low quality (junk) portfolios. To volatility-manage the sector neutral strategies, the daily returns of the sector neutral QMJ are used to create a variance forecast. Then strategy exposure is scaled depending on a volatility target and the volatility forecast for each month.



6. Robustness Tests

In this chapter we present robustness tests for the results from Chapter 4 and 5. We conduct an analysis of industry quality effects within QMJ, by sorting stocks into 48 industries instead of ten sectors. We perform the same tests as in Chapter 4 and 5. This is to ensure that our results are robust to a narrow industry definition. In Table 10, we present a summary of the results. We only present the 6-factor alphas and factor loadings, as we consider them as the most relevant for a comparison to the sector results. More detailed results are available upon request. We follow the same methodology as in Chapter 4 and 5, but we require six observations for an industry to be included in the return tests each month.

For the *within-industry* test, we find that the QMJ only yields significant 6-factor alpha in one out of 48 industries. Similarly, the *within-sector* test yield significant alpha for only two out of ten sectors. Furthermore, the results of the *random industry* test are similar to the results of the *random sector* test. We find that six out of 48 random industry portfolios yield significant 6-factor alpha, an increase from the *within-industry* test. Six out of 48 industries is a low fraction, which might indicate sector quality effects are present. However, the number of industries delivering positive abnormal returns increases compared to the *within-industry* test, making interpretations unclear and the results inconclusive. Still, the results suggest industry quality effects are not the *only* driver of QMJ abnormal returns. Moreover, when we assign stocks to random industry portfolios, 6.2% of the stocks are on average still within the same industry portfolio. When we assign stocks to random sector portfolios, 16.3% of the stocks are on average still within the same sector portfolio. This might indicate that an industry sort is better suited for this test.

Table 10 provides further confirmation that our results are robust to a narrow industry definition. For the industry demeaned QMJ, we demean individual stock quality with average industry quality and observe some deviations from the *sector demeaning* test. The abnormal returns are unchanged, but the Sharpe ratio drops by 40%. As the performance of the strategy is reduced, the *industry demeaning* test might suggest industry quality effects drive QMJ abnormal returns. This is in contrast to the results of the *sector demeaning* test, which indicates sector quality effects are not present within QMJ.

For the *long junk – short quality* test, we follow the methodology of Asness et al. (2000). We examine a strategy that is long the junk quintile of the seven industries that score highest on quality and short the quality quintile of the seven industries that score lowest on quality. The strategy delivers a positive insignificant 6-factor alpha. Hence, this result is not as strongly in favour of industry quality effects driving abnormal returns as the equivalent sector test. However, for this test to suggest that individual stock quality drives QMJ abnormal returns, we should see negative and significant alphas.

We also create an industry neutral QMJ, using CRSP value-weighted target industry weights. This strategy yields a 6-factor alpha of 0.14% compared to 0.22% for the unrestricted QMJ. By removing the possibility to bet on industries, strategy performance is reduced. Therefore, this test indicates that industry quality effects drive QMJ abnormal returns.

At last, we volatility-manage the industry neutral QMJ and confirm that it produces large significant abnormal returns. As presented in column 6 of Table 10, the 6-factor alpha is restored, and Sharpe ratio nearly doubles by managing the volatility of the industry neutral QMJ. This confirms the results we document in Chapter 4 and 5 holds for a narrow industry definition.

Table 10
Summary of Robustness Tests

This table presents the results of the 6-factor regressions on the QMJ, industry demeaned QMJ, Long junk – Short quality for industries, industry neutral QMJ and volatility-managed industry neutral QMJ (5% volatility target). The sample runs from July 1963 through December 2016. The construction of portfolio returns follows the same methodology utilized in Chapter 4 and 5. Alphas are reported with respect to the 6-factor model, and t-statistics are presented under the estimates in parentheses. The explanatory variables in the time-series are the returns of the market (MKT), size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), and momentum (UMD) portfolios from Ken French's data library. The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported in monthly percent. Sharpe ratios are annualized. Significant alphas and excess returns at the 5% level are reported in bold.

	QMJ	Demeaned QMJ	Long junk Short quality	Industry neutral QMJ	Vol.managed 5%
Excess return	0.12	0.07	-0.05	0.10	**0.15**
	[1.33]	[0.81]	[-0.24]	[1.27]	[2.16]
6-factor alpha	**0.22**	**0.20**	0.07	**0.14**	**0.20**
	[3.71]	[3.63]	[0.33]	[2.29]	[3.53]
MKT	-0.15	-0.19	0.21	-0.11	-0.07
	[-10.25]	[-14.16]	[4.13]	[-7.24]	[-5.09]
SMB	-0.08	-0.15	0.24	-0.17	-0.14
	[-3.85]	[-7.92]	[3.42]	[-8.58]	[-7.67]
HML	-0.40	-0.37	-0.05	-0.23	-0.16
	[-14.05]	[-13.70]	[-0.47]	[-7.93]	[-6.16]
CMA	-0.11	-0.01	-0.36	-0.03	-0.06
	[-2.69]	[-0.26]	[-2.51]	[-0.79]	[-1.69]
RMW	0.42	0.34	-0.37	0.32	0.25
	[14.99]	[13.31]	[-3.83]	[11.37]	[9.68]
MOM	0.11	0.09	-0.02	0.13	0.07
	[8.33]	[7.06]	[-0.46]	[9.07]	[5.13]
Sharpe ratio	0.18	0.11	-0.03	0.18	0.30

7. Conclusion

In this thesis we test whether sector quality effects drive QMJ abnormal returns. We follow the methodology of Moskowitz and Grinblatt (1999), and perform a battery of tests on QMJ to determine whether the strategy invests in sectors that outperform rather than individual quality stocks.

First, we test whether the QMJ strategy yields a significant alpha within sectors. We find that only two out of ten sectors yield a significant 6-factor alpha, which indicates sector quality effects drive the QMJ abnormal returns. Moreover, we test whether demeaning the QMJ strategy by average sector quality score affects the performance of the QMJ. Our results show that demeaning has a negligible effect on abnormal returns and Sharpe ratios, which indicates that sector quality effects is not the driver of the abnormal returns of the QMJ strategy.

Next, we create random sector portfolios to isolate the sector quality effects within QMJ. We document that a majority of the random sectors do not yield significant alphas. This indicates that sector quality effects are not the only driver of QMJ abnormal returns. We proceed to create strategies that are long junk stocks from the highest quality sectors, and short quality stocks from the lowest quality sectors. The strategies yield positive and significant 5-factor alphas, which suggests that sector quality effects drive QMJ abnormal returns. As a final test, we create sector neutral QMJ portfolios. We find that the sector neutral QMJ strategies perform worse than the unrestricted QMJ in return tests, yielding substantially lower abnormal returns. By removing the possibility to bet on sectors, strategy performance is reduced. Therefore, this test indicates that sector quality effects drive QMJ abnormal returns.

A majority of the tests point towards there being sector quality effects within the QMJ factor. Due to contradicting result from the *sector demeaning* test and the *random sector* test, it is unlikely that only sector quality effects drive the QMJ abnormal returns. Therefore, we conclude sector quality effects partially drive the abnormal returns of the QMJ strategy. This implies the QMJ strategy lacks diversification and could serve as a potential explanation of the quality puzzle.

In an attempt to refute this potential explanation of the quality puzzle, we manage the volatility of the sector neutral QMJ following the methodology of Barroso and Santa-Clara (2015). By dynamically scaling strategy exposure, we are able to create QMJ strategy which is not allowed to bet on sectors, that delivers abnormal and excess returns in the same magnitude as the unrestricted QMJ strategy. The volatility-managed sector neutral QMJ strategy with a 12% volatility target delivers 6-factor alpha of 0.40%, compared to 0.09% and 0.22% for the sector neutral and unrestricted QMJ respectively. Hence, we provide a QMJ strategy that is more diversified than the unrestricted QMJ that still delivers high abnormal returns.

In summary, we find that sector quality effects partially drive QMJ abnormal returns. This is a potential risk-based explanation for the QMJ abnormal returns, as it indicates lack of diversification in the strategy. However, we document that a volatility-managed sector neutral QMJ strategy, which does not suffer from lack of diversification, yields significant abnormal returns in the 6-factor model. These results are robust to a narrow industry definition. This makes the QMJ abnormal returns harder to explain and deepens the quality puzzle.

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9. Appendix

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

Working capital = Current assets – Current liabilities – Cash and short-term instruments + Short term debt + Income taxes payable

Book equity = Shareholders' equity – Preferred stock (PSTKRV, PSTKL or PSTK depending on availability)

If shareholders' equity is not available, the following is used:

Shareholders' equity = Common equity + Preferred Stock

We proxy shareholders' equity by Total assets – (Total liability + Minority Interest) if both Common equity and Preferred stock is missing.

Growth Measures:

ΔGPOA = (Gross Profits$_t$ – Gross Profits$_{t-5)}$ / Total assets$_{t-5}$

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 = (Cash Flow$_t$ – Cash Flow$_{t-5}$) / Total assets$_{t-5}$, where Cash Flow = Net income + Depreciation – Changes in working capital – Capital expenditures.

ΔGMAR = (Gross Profits$_t$ – Gross Profits$_{t-5)}$ / Total sales$_{t-5}$

Safety Measures:

Beta estimate (BAB) = $\beta_i = \frac{\sigma_i}{\sigma_m}\rho$,

where σ_i and σ_m are the estimates for standard deviation for the stock and the market, and ρ is their correlation

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

Ohlson's O-score = - (-1.32 – 0.407 * log (ADJASSET/CPI) + TLTA – 1.43 * WCTA + 0.076 * CLCA – 1.72 * OENEG – 2.37 * NITA – 1.83 * FUTL + 0.285 *INTWO – 0.521 * CHIN)

Adjusted assets = Assets total + 0.1 * (Market equity – Book equity)

CPI = Consumer price index

TLTA = Book value of debt (DLC + DLTT) / Adjusted assets

WCTA = (Current assets – Current liabilities) / Adjusted assets

CLCA = Current liabilities / Current assets

OENEG is dummy equal to 1 if total liabilities exceed total assets

NITA = Net income / Total assets

FUTL = Pre-tax income / Total liabilities

INTWO is a dummy equal to one if net income is negative for the current and prior fiscal year.

CHIN = Changes in net income = (Net income$_t$ – Net income$_{t-1}$) / (|Net income$_t$| + |Net income$_{t-1}$|)

Altman’s Z-score = (1.2 * Working capital + 1.4 * Retained earnings + 3.3 * Earnings before interest and taxes + 0.6 * Market equity + Total sales) / Assets total

EVOL = Standard deviation of quarterly ROE over the past 60 quarters. We require 12 non-missing quarters. If we are missing quarterly data, we use annual ROE over the past five years, where we require at least five non-missing fiscal years.

List of variables

The variables names presented as abbreviations corresponding to the variable abbreviation in the CRSP and Compustat datasets.

Merged CRSP/Compustat

Data type: Annual/Quarterly

Data range: July 1957 through December 2016

SIC	TXP	NI	DLTT	FYEAR	FYR
First effective date of link	REVT	DVP	MIBT	GIND	RE
Last effective date of link	COGS	GP	PI	GSECTORS	DVP
Historical CRSP Permno link	SEQ	DP	REVT	STKO	EXCHG
Fiscal year-end	PSTK	CAPX	EBIT	LINKDT	DLV
FYEAR – Date Year – Fiscal	LT	WCAP	CH	LINKENDDT	ACT
AT	MIB	WCAPCH	LCT	LPERMCO	PSTKL
CEQ	PSTKRV	SALE	CHE	LPERMNO	IB

CRSP

Data type: Monthly/Daily

Data range: July 1957 through December 2016

PERMNO	RET
DATE	SHROUT
SHRCD	DLSTCD
EXCHCD	DLRET
SICCD	VWRETD
PRC	

List of sectors

We use GIC codes to assign firms to 11 sectors. The following list contains the GIC codes that defines each sector.

Energy	10
Materials	15
Industrials	20
Consumer Discretionary	25
Consumer Staples	30
Health Care	35
Financials	40
Information Technology	45
Communication Services	50
Utilities	55
Real Estate	60

List of industries

We use digit SIC codes to assign firms to 48 industries. The following list contains the range of SIC codes that defines each industry (Asness et al., 2000).

Agriculture	0100-0799, 2048-2048
Food Products	2000-2046, 2050-2063, 2070-2079, 2090-2095 2098-2099
Candy and Soda	2064-2068, 2086-2087, 2096-2097
Alcoholic Beverages	2080-2085
Tobacco Products	2100-2199
Recreational Products	0900-0999, 3650-3652, 3732-3732, 3930-3949
Entertainment	7800-7842, 7870-7870, 7900-7999
Printing and Publishing	2700-2749, 2770-2799
Consumer Goods	2047-2047, 2391-2392, 2510-2519, 2590-2599, 2840-2844, 3160-3199, 3229-3231, 3260-3260, 3269-3269, 3630-3639, 3750-3751, 3800-3800, 3860-3879, 3910-3919, 3960-3964, 3970-3970, 3991-3991, 3995-3995
Apparel	2300-2390, 3020-3021, 3100-3111, 3130-3159, 3965-3965
Healthcare	8000-8099
Medical Equipment	3693-3693, 3840-3851
Pharmaceutical Products	2830-2836
Chemicals	2800-2829, 2850-2899
Rubber and Plastic Products	3000-3000, 3050-3099
Textiles	2200-2295, 2297-2299, 2393-2395, 2397-2399 30
Construction Materials	0800-0899, 2400-2439, 2450-2459, 2490-2499, 2950-2952 3200-3219, 3240-3259, 3261-3261, 3264-3264, 3270-3299 3420-3442, 3446-3452, 3490-3499, 3996-3996
Construction	1500-1549, 1600-1699, 1700-1799
Steel Works	3300-3370, 3390-3399
Fabricated Products	3400-3400, 3443-3444, 3460-3479
Machinery	3510-3536, 3540-3569, 3580-3599
Electrical Equipment	3600-3621, 3623-3629, 3640-3646, 3648-3649, 3660-3660, 3690-3692, 3699-3699
Miscellaneous	3900-3900, 3990-3990, 3999-3999, 9900-9999
Automobiles and Trucks	2296-2296, 2396-2396, 3010-3011, 3537-3537, 3647-3647, 3694-3694, 3700-3716, 3790-3792, 3799-3799

Aircraft	3720-3729
Shipbuilding, Railroad	3730-3731, 3740-3743
Defence	3480-3489, 3760-3769, 3795-3795
Precious Metals	1040-1049, 1101-1101
Non-Metallic Mining	1000-1039, 1060-1099, 1400-1499
Coal	1111-1111, 1200-1299
Petroleum and Natural Gas	1110-1110, 1310-1390, 2900-2911, 2990-2999
Utilities	4900-4999
Telecommunications	4800-4899
Personal Services	7020-7021, 7030-7039, 7200-7212, 7214-7299, 7395-7395 7500-7500, 7520-7549, 7600-7699, 8100-8199, 8200-8299 8300-8399, 8400-8499, 8600-8699, 8800-8899
Business Services	2750-2759, 3993-3993, 7300-7372, 7374-7394, 7396-7397 7399-7399, 7510-7519, 8700-8799, 8900-8999
Computers	3570-3579, 3680-3689, 3695-3695, 7373-7373
Electronic Equipment	3622-3622, 3661-3679, 3810-3810, 3812-3812
Measuring and Control Equip.	3811-3811, 3820-3832
Business Supplies	2520-2549, 2600-2639, 2670-2699, 2760-2761, 2950-2955
Shipping Containers	2440-2449, 2640-2659, 3210-3221, 3410-3412
Transportation	4000-4099, 4100-4199, 4200-4299, 4400-4499, 4500-4599 4600-4699, 4700-4799
Wholesale	5000-5099, 5100-5199
Retail	5200-5299, 5300-5399, 5400-5499, 5500-5599, 5600-5699 5700-5736, 5900-5999
Restaurants, Hotel and Motel	5800-5813, 5890-5890, 7000-7019, 7040-7049, 7213-7213
Banking	6000-6099, 6100-6199
Insurance	6300-6399, 6400-6411
Real Estate	6500-6553, 6590-6590
Trading	6200-6299, 6700-6799