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Is There a Flight to Quality?

A study on Flight to Quality within the Equity Markets

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Abstract

Much of the research on flight to quality use different definitions of "flight" and "quality", making the findings difficult to compare. The coherent story behind this phenomenon is that investors become risk-averse during market distress and flee to safer asset classes. In this thesis, we test whether there is a flight to quality within the equity markets, using a broadly accepted definition of quality and institutional investor holdings data. We measure the portfolio share of institutional investors that are allocated in high- and low-quality stocks and compare it to the market share of high- and low-quality stocks. We find that both the market share of quality stocks and the investor bet on quality increase during recessions. We look at the active bets investors make in quality stocks by subtracting the market share of quality. We find evidence that there is a flight to high-quality stocks during recessions but we do not find evidence that investors flee low-quality stocks. We also find that investors seek quality stocks, but do not only look at safety characteristics. This thesis extends the financial literature on the topic of flight to quality to include the equity markets.

Contents

1 Introduction **1**

2 Literature Review **5**

3 Data and Methodology **10**
- 3.1 Data Sources for QMJ . . . 10
- 3.2 Data Cleaning . . . 12
- 3.3 Quality Score . . . 14
- 3.4 Portfolio Formation . . . 15
- 3.5 Recessions and Investor Herding . . . 18

4 Empirical Analysis **22**
- 4.1 QMJ during Recessions . . . 22
- 4.2 Investor bets on Quality . . . 24
- 4.3 Deliberate or Involuntary? . . . 31
  - 4.3.1 Quality Ratio . . . 31
  - 4.3.2 Junk Ratio . . . 35
  - 4.3.3 QMJ Ratio . . . 37
  - 4.3.4 Adjusted Quality Ratio . . . 39

5 Robustness **43**
- 5.1 Pruned Quality Ratio . . . 43
- 5.2 Negative Return Periods . . . 45
- 5.3 Flight to Profit, Growth or Safety? . . . 46

6 QMJ and Momentum **52**
- 6.1 QMJ as Risk Mitigation for WML . . . 52
- 6.2 Results and Implications . . . 54

7 Discussion **57**

8 Conclusion **59**

References **60**

Appendix **62**

A Appendix A: Formulas for Replicating QMJ **62**
- A1 Accounting Variables . . . 62
- A2 Profitability . . . 63
- A3 Growth . . . 63
- A4 Safety . . . 64

B Appendix B: List of Variables **66**

C Appendix C: Replication of Barroso and Santa-Clara **67**

List of Figures

4.1 **Market Share of Quality and Junk Stocks Over Time** 28
4.2 **Mean Quality and Junk Ratio of the Institutional Investors Over Time** 29
4.3 **Quality and Junk Ratios Adjusted for Their Market Shares** . . . 30
6.1 **Annualized Mean Return of Strategies** 55

List of Tables

3.1 **QMJ Replication** . . . 18
4.1 **QMJ during Recessions and High Volatility Environment** . . . 23
4.2 **Quality and Junk during Recessions and High Volatility Environment** . . . 24
4.3 **Descriptive Statistics** . . . 26
4.4 **Change in Quality Ratio Regression** . . . 33
4.5 **Delta Junk Ratio Regression** . . . 36
4.6 **Delta QMJ Ratio Regression** . . . 38
4.7 **Delta Adjusted Quality Ratio Regression** . . . 41
5.1 **Pruned Delta Quality Ratio** . . . 44
5.2 **Change in Quality Ratio Regression with Negative Return Dummy** 47
5.3 **Delta Growth Ratio** . . . 49
5.4 **Delta Profitability Ratio** . . . 50
5.5 **Delta Safety Ratio** . . . 51
6.1 **Results with Scalar** . . . 56
A0.1 **Compustat Variables** . . . 66
A0.2 **CRSP Variables** . . . 66
A0.1 **Replication of Barroso and Santa-Clara Scalar** . . . 67

1 Introduction

In earlier research, the notion of *flight to quality* during recessions has been proven predominantly by comparing the relationship between investor preference for equity markets and treasury bonds. While researchers, to a large extent, seem to agree that there is a *flight to quality*, both the definition of "flight" and "quality" varies among the papers. The coherent story behind this phenomenon is that investors become risk-averse during recessions and flee to safer asset classes. However, one does not have to flee equity markets to move into safer assets, as some stocks are safer than other stocks in terms of bankruptcy risk, profitability risk, and volatility. Likewise, certain stock characteristics like profitability, growth, and safety are used to proxy the quality of stocks. If there is a *flight to quality*, does it occur within the equity markets?

Inci et al. (2011) define *flight to quality* as "a pronounced and generally rapid increase in risk aversion" and measure the correlation between U.S. spot market and U.S. treasury bonds during recessions. They find that as market risk grows, investors become more risk-averse and move much of their capital from the equity markets to U.S. treasury bonds. Brière et al. (2012), who also look at the correlation between different asset classes, claim that there is no doubt of *flight to quality* during crises. However, none of the studies looks within the equity markets. What is the reaction of the investors who stay invested in the equity markets? Are the funds moved into safer stocks?

In this thesis, we seek to test if the notion *flight to quality* is pervasive and occurs within the equity markets. There is more than one definition of quality, making it a challenge to conclude that the flight is attributed to quality in itself rather than the interchangeable definition of quality and the endogenous characteristics of the assets. Choi and Sias (2009) find evidence that investors follow each other and herd to the same stocks. We hypothesize that institutional investors herd into safe, high-quality stocks and out of risky, low-quality stocks during recessions. To test this, we need to identify the quality stocks the investors should herd into, using a broadly accepted definition of quality.

We examine the literature on quality characteristics and argue that the quality measure introduced by Asness et al. (2019) is the most suitable quality measure to test the hypothesis with. Asness et al. (2019) present a quality definition comprised of multiple quality measures that derive from the extensive literature on quality pricing anomalies. They combine safety, profitability, and growth measures into one quality measure and develop a self-financed Quality Minus Junk (QMJ) investment strategy that goes long, high-quality stocks and short low-quality stocks. They find that QMJ generates significant alphas that are robust to conventional asset pricing models. Furthermore, the QMJ strategy performs well and sustains low volatility during recessions. Asness et al. (2019) attribute the high performance during recessions to investor *flight to quality*. However, it is vaguely inferred and not tested.

We then replicate the U.S. QMJ factor returns to mitigate a potential size bias when identifying quality stocks. All stocks are assigned a quality score, and the 30% highest (lowest) ranked stocks within small and large firms are classified as quality (junk) stocks. We find a monthly 6-factor alpha for the QMJ strategy of 0.21%, compared to 0.33% in the original paper. All factor loadings follow the same direction as in the original paper except for the momentum factor, which is negative. The replicated QMJ also shows statistically significant abnormal returns for each individual quality measure. For the purpose of this thesis, the results suggest that the replication is successful.

Next, we look at institutional investor holdings from the Thomson quarterly 13f filings from December 1998 to December 2019, to answer our research question. We assign the stocks in the holdings the quality scores received when replicating the QMJ and measure the relative weight institutional investors invest in quality and junk stocks. On average, institutional investors invest 35% and 13% of their stock portfolios in quality and junk stocks, respectively. We refer to this as the investor's quality and junk ratio. This is higher than the 28% and 11% average market share of quality and junk stocks. These results imply that investors slightly favour quality and junk stocks. In other words, they seem to invest in quality and junk stocks deliberately and not follow a general diversification strategy.

To test if there is a *flight to quality* during recessions, we use the NBER definition of recession to identify the recession quarters, similar to Asness et al. (2019). Every quarter that includes a recession month is classified as a recession and assigned a dummy variable equal to one. We then measure the change in investor quality ratios. We find that both the market share of quality stocks and investors' quality ratio increase during recessions.

On average, quality stocks account for 30% of the total market during recessions, whereas the average quality ratio increases to 39%. We regress the change in quality, junk, and QMJ ratio over the time sample. We find evidence of a *flight to quality* within the U.S. equity markets during recessions. However, we find that the change in junk ratio is minor and cannot be attributed to recessions, suggesting that there is no "flight from junk". This is unexpected as it implies that investors sell other stocks than junk to buy more into quality.

As the increase in market share can mechanically drive up the quality ratio of the investors, we adjust for it by subtracting the market share of quality stocks from the quality ratio. This allows us to estimate investors' active bets on quality. The results are similar after the adjustment, supporting the claim that there is a *flight to quality* within the equity markets.

To challenge the notion and see if the flight can be attributed to safety, we conduct robustness tests using the quality measures profitability, growth, and safety individually when ranking the stocks. Contrary to what is expected, we find no evidence that investors herd to stocks ranked on the safety component individually. This implies that although there is a *flight to quality*, investors look for other characteristics in stocks such as profitability and growth during recessions. The recession dummy shows the largest economic magnitude when combining all three quality measures, suggesting that evidence flight to quality is strongest when using multiple quality measures.

In this thesis, we contribute to the existing literature of *flight to quality* by testing the phenomenon in the equity markets. Although our findings support the notion *flight to quality*, we find no evidence that there is a flight from junk. Furthermore, we do not find evidence that investors herd to quality stocks because the stocks are safe. This opens up the possibility that the herding to quality is due to endogenous characteristics found in quality stocks. It is also unclear whether investors herd to quality stocks because the stocks perform well or whether the stocks perform well because of the herding. There could be a behavioural explanation behind the herding.

Knowing that the QMJ strategy performs well and sustains low volatility during recessions, we test the viability of using QMJ to mitigate the crash risk of the winners-minus-losers (WML) momentum strategy documented by Daniel and Moskowitz (2016). The test is separate from the flight to quality test, as the results are independent of the outcome. The purpose of this test is to expand the understanding of quality and momentum returns. The goal is not to find the best way of combining QMJ and WML but rather to see if QMJ can be used in a simple construct to mitigate the crash risk of WML. A 50/50 weight scheme gives an annualized Sharpe ratio of 0.64, lower than the 0.86 Sharpe ratio Asness et al. (2013) find when they combine momentum with value. We develop a dynamic QMJ-WML joint-strategy portfolio that uses a volatility scalar introduced by Barroso and Santa-Clara (2015) to adjust the weight between QMJ and WML. Our dynamic portfolio gives an annualized Sharpe ratio of 1.01 and mitigates major crashes in returns. In short, our findings suggest that QMJ could be used to mitigate the risks and increase the Sharpe ratio of momentum strategies.

The thesis is organized as follows: Chapter 2 presents literature relevant to this thesis and reviews the literature on quality. Chapter 3 shows the relevant data sources, replication of the QMJ factor, and methodology. Chapter 4 contains our empirical analysis where we answer our research question. In chapter 5, we examine the robustness of our findings. In chapter 6, we test whether QMJ can help mitigate the risk of momentum strategies. In chapter 7, we discuss the findings. Lastly, in chapter 8, we conclude our thesis.

2 Literature Review

Numerous papers look at investor *flight to quality* during market downturns, market distress, or when the economic forecast sentiment is low. Inci et al. (2011) investigate the *flight to quality* phenomenon by using treasury bonds as a quality proxy or safe asset class. The evidence suggests there is a *flight to quality* as the correlation between treasury bonds and the stock market during crashes is negative (Inci et al., 2011). In other words, they find that investors leave the U.S. spot market for the U.S. treasury bond market during market downturns. Brière et al. (2012) find evidence that the *flight to quality* effect remains after taking globalization into account. Brière et al. (2012) find that the correlation among equity markets increases while the correlation between the equity and bond markets decrease. Both studies use the notion *flight to quality* to describe the investor flow from equity to safer asset classes during market downturns. However, neither of the studies looks at investor behavior within one specific asset class. The argument that investors flee from riskier to safer asset classes does not reject the idea that investors flee to safer assets in general. As some firms are safer than other firms in terms of bankruptcy risk, profitability risk, and exposure to systematic risk, a *flight to quality* also implies that there could be a flight from riskier to safer stocks. This thesis extends the current financial literature by testing whether investors flee to quality within the equity market during recessions.

Many authors use different definitions or inferences of flight to quality, making it a challenge to understand what *flight to quality* means and whether the notion is being misused. Beber et al. (2008) use data on the Euro-area government bond market to refute the idea that investors flee to quality during market downturns. They find evidence that most of the largest inflows of funds into the Euro-area bond market occurs when the economic sentiment indicator is negative for economic prospects. Their findings support the influx of money into government bonds during market distress. However, they distinguish between credit quality and liquidity and find that investors chase liquidity during market distress, not credit quality (Beber et al., 2008). Beber et al. (2008) look within the Euro-area bond market and use a different definition of quality than Inci et al. (2011) who compare two different asset classes. Vayanos (2004) proposes a theory of time-varying liquidity premia, based on the assumption that fund managers are subject to withdrawals when fund performance falls below a threshold. Vayanos (2004) finds evidence that financial assets' liquidity premia increase during market downturns. Further, the notion *flight to quality* is inferred by investors becoming more risk-averse and demanding a higher risk premium per unit of volatility during market downturns (Vayanos, 2004). It can be difficult to conclude a *flight to quality* when the proxy for quality is interchangeable, and several studies compare different asset classes to each other.

To investigate the notion of *flight to quality* within equities, we need to use a quality measure that is robust and comprised of implicit and explicit understandings of what quality is. We look at current financial literature and studies to determine which quality proxy is best suited for testing the research question. Earlier literature use safer asset classes as a proxy for quality during recessions. Bernanke et al. (1996) find evidence that access to credit is impaired for firms that have a high agency cost during recessions. This is a consequence of the fact that borrowers want to lend money to "safer" firms with lower bankruptcy risk; hence the *flight to quality* is inferred (Bernanke et al., 1996). Their findings imply that low-quality firms are at greater risk of bankruptcy and should underperform during economic downturns relative to other stocks.

Novy-Marx (2013) looks at the quality of profitability measures and finds that profitable firms outperform unprofitable firms. Novy-Marx (2013) introduces the gross-profits-to-assets measure and finds evidence that it is a strong predictor of the cross-section of expected returns. Fama and French (2006) find that profitable firms have a higher expected return using the dividend discount model. Chan et al. (2006) dissect the reported earnings of firms and find evidence that the earnings increases with high accruals are associated with low future returns. They suggest that high accruals generally mean low quality of earnings. Mohanram (2005) finds evidence that high-growth firms do better than low-growth firms. These are a few of the studies that try to explain the abnormal returns of quality characteristics. The consistent findings that profitable and high-growth stocks make a good case for why we should include these measures when identifying quality firms.

Frazzini and Pedersen (2014) document that firms with low beta generate high alphas. In other words, low-risk stocks generate high abnormal returns. One possible explanation for this phenomenon is that constrained investors invest more in high-beta stocks, thus, pushing up the price and lowering the return of high-beta stocks (Frazzini and Pedersen, 2014). Furthermore, George and Hwang (2010) find evidence that stocks with low leverage and financial distress exert higher risk-adjusted returns. Because much of the literature about flight to quality suggests that investors move to safer asset classes, one can argue that the safety component is a crucial characteristic of quality stocks.

Asness et al. (2019) introduce the Quality Minus Junk (QMJ) strategy, based on a quality proxy synthesized by three quality factors: profitability, growth, and safety. The QMJ strategy is built on various financial formulas and research and is arguably one of the more comprehensive and broadly accepted quality measures for stocks. Furthermore, Asness et al. (2019) find that the quality factor generates high alphas that conventional asset pricing models do not explain. The quality pricing anomaly is difficult to explain using risk-based explanations, as profitable, growing, safe firms are deemed less risky. In fact, it is puzzling how something less risky would be able to sustain abnormal returns over a long period. Asness et al. (2019) find that high-quality firms exhibit high risk-adjusted returns. Further, while open to it, the authors refute a risk-based explanation by providing empirical evidence of the opposite. Quality stocks are underpriced and safer, while junk stocks are overpriced and riskier, providing a significant abnormal return for the QMJ strategy (Asness et al., 2019). Asness et al. (2019) suggest that the quality puzzle is either a pricing anomaly, an unidentified risk factor, or derived from data mining.

Even when accounting for a higher t-stat requirement as suggested by Harvey et al. (2015), the QMJ is robust. Due to the old age of financial theory, data mining is becoming a more significant part of the theoretical reality, and factors should pass a higher t-stat hurdle before being accepted (Harvey et al., 2015). The strongest evidence against a risk-based explanation Asness et al. (2019) gives is that the quality stocks and QMJ strategy perform well during extreme market distress. This is assumed by the authors to come from a flight to quality (Asness et al., 2019). These findings and inferences, in combination with the fact that QMJ is both robust and aligned with the understanding of what "quality" means, suggest that if there is a *flight to quality* during recessions, the quality measure from the QMJ strategy is the most suitable proxy to use within the equity markets. Therefore, we choose to conduct this study using the quality measure constructed by Asness et al. (2019).

We look at institutional investors and their changes in portfolio holdings over time to test the flight behavior. Choi and Sias (2009) find evidence that institutional investors herd into and out of the same industries. Their findings suggest that the most significant contributor to industry herding is the herding of institutional investors into the same stock. The evidence suggests that the investors follow each other rather than themselves (Choi and Sias, 2009). Their findings imply that more should follow if some institutional investors flee to quality within the equities during market downturns. Therefore, it makes sense to investigate whether the *flight to quality* phenomenon exists in equity markets by looking at institutional investor behavior.

This thesis extends the research on the *flight to quality* phenomenon to include the equity markets. Although many present findings of a *flight to quality* effect, the definition of "quality" is not consistent and often refers to government bonds. There is ample evidence of a flight out of equity markets during market distress, and it is often referred to as a *"flight to quality"*. This seems to be accepted as conventional knowledge and not refuted. The findings of Beber et al. (2008) suggest that there may be another story behind the flight. Furthermore, we help explain the institutional investors' behavior and (lack of) awareness of quality stocks and performance during market downturns. As Vayanos (2004) logically assumes that institutional investors are subject to withdrawals during market distress, investors may look for something other than quality. Thus, it is not apparent that investors flee to quality firms during recessions. Due to the challenge in comparing various definitions of *flight to quality* and proxies for quality, this thesis uses an accepted quality proxy as it can prove imperative to the findings. Our findings either conclude that there is a *flight to quality* during recessions or extend the financial literature and open up new areas of research.

This thesis contributes to the understanding of market behavior and institutional investor behavior during recessions. We show the role institutional investors play in explaining the abnormal returns of quality stocks. The contribution can help de-mystify and provide a behavioral-driven explanation to the quality puzzle. The assumption Asness et al. (2019) make about QMJ benefiting from a *flight to quality* is vaguely inferred and not tested in the equity markets. We test the *flight to quality* assumption in the equity markets by using their definition of quality. To assert their assumption directly, we need to identify the same quality and junk stocks as they do. Fama and French (1993) find that larger stocks are on average less risky than smaller stocks, implying that we need to adjust for the size effect to mitigate potential size biases. We mitigate the potential size effect by replicating the QMJ factor using the methodology presented in the original paper.

As an additional contribution to the research on momentum investment strategies, we test whether the QMJ strategy can be used to mitigate the risk of the winners-minus-loser (WML) strategy. Daniel and Moskowitz (2016) find that although momentum strategies exhibit strong positive averages, they are sensitive to market declines and sometimes crash. The infrequent crashes eradicate the long-term profits generated by WML (Daniel and Moskowitz, 2016). Barroso and Santa-Clara (2015) introduce a scalar that uses the historical variance of the WML returns to scale up or down. They find that the WML strategy returns can be drastically improved in terms of return per risk unit (Sharpe) and the crashes can be mitigated. Asness et al. (2013) find that creating a joint-strategy portfolio with value and momentum generates a significantly higher Sharpe ratio than either of the strategies individually. By combining the QMJ and WML strategies, we contribute to understanding the usability and performance of QMJ in joint-strategy portfolios and risk-mitigation of momentum strategies.

3 Data and Methodology

Firstly, we need to define quality. In this paper, we create the Quality minus Junk factor of Asness et al. (2019), which is both robust and performs well during recessions, and mitigates size effects. The quality (and junk) definition is used to calculate institutional investors' quality (and junk) ratio used for our empirical analysis. In addition, the QMJ factors' volatility is used as an independent variable for regressions later on. Secondly, to test if there is a flight to quality, we investigate the investors' holdings of quality stocks. Investors' holdings are not readily available, with some exceptions. One being the 13f filings, required to be filed every quarter by institutional investors. Choi and Sias (2009) uses 13f filings and finds industry herding, and arguably if quality herding exists, one would see it in this data.

In this section, we present our data sources, the cleaning processes, the portfolio formation, and the specific assumptions made to replicate the factor and demonstrate that the replication is successful and, hence, a valid quality proxy to answer the research question. Firstly, we describe our data sources, the cleaning process, and the construction of quality stocks described in the original paper. Secondly, we construct QMJ factor returns similar to tables 4 and 5 in the original paper of Asness et al. (2019). Lastly, we describe how the quality measure is used to calculate the investor's quality ratio and how it is utilized in the empirical analysis.

3.1 Data Sources for QMJ

The replication of the QMJ factor follows the methodology of Asness et al. (2019) as closely as possible in order to compare it to the original results and demonstrate that the replication is successful. The sample for the replication of the QMJ factor runs from June 1950 to December 2016 and contains U.S. stocks only.[1] Daily and 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.

[1]Although Asness et al. (2019) state that the data sample period is from June 1957, the QMJ portfolio returns run from July 1957. Because the growth factors require six years of accounting data, and the portfolios are formed in June, the year after reporting, we include data from 1950.

We use all common stocks listed on the NYSE, AMEX, and NASDAQ[2] except for REIT funds (SIC 6798). We include financial firms because there is no indication of Asness et al. (2019) removing them. At this stage, we have 246 588 annual observations and 16 228 unique stocks in the merged CRSP/Compustat North America data. We follow the standard convention of Fama and French (1992) and align the accounting variables from Compustat with the firm's fiscal year ending between July year *t-1* to June year *t*, to June year *t*.

For the CRSP monthly dataset, we follow the methodology of Asness et al. (2019) and include delisting returns when available. If a firm is delisted and the delisting return is performance-related, the return is assumed to be -30%. These adjustments are made to adjust for delisting biases that occur when firms are delisted (Shumway, 1997). However, we find no missing delisting returns where this is applicable. We only include common stocks that have return data.

Factor returns are downloaded from Kenneth French's data library (2021). The risk-free monthly returns are downloaded from AQR's data library, also found on Frazzini's data library (2021). The first available portfolio formation is in June 1957.

QMJ is a combined quality measure consisting of three overarching factors comprised of 16 individual measures. The profitability factor consists of six different profitability measures: gross profits over assets (GPOA), return on equity (ROE), return on assets (ROA), cash flow over assets (CFOA), gross margin (GMAR), and accruals (ACC). The growth factor is a five-year growth measure in residual profits of all profitability measures except accruals. The safety factor consists of five safety measures: beta (BAB), leverage (LEV), bankruptcy risk (Ohlson's O and Altman's Z), and earnings volatility (EVOL).

The data found on Kenneth French's website and AQR's data library are continuously updated and may be different from when the original paper was published. In addition, AQR specifies that there might be differences in data sources and methodology. Further, some pre-processing steps and assumptions are not explicit in the original paper. This makes it challenging to replicate exact results for QMJ.

[2]Merged CRSP/Compustat exchange code 11, 12, 14, and CRSP exchange code 1, 2, 3

3.2 Data Cleaning

We follow the methodology of Asness et al. (2019) to the extent possible when constructing the quality measures. Because some measures are constructed using accounting variables that may be missing in the merged CRSP/Compustat data, many values will naturally be unavailable. Therefore, some data cleaning is necessary not to lose too many observations. In this section, we describe the assumptions and adjustments we make to replicate the QMJ factor. Formulas for every quality factor and input variables are found in the appendix.

We start by looking at the profitability measures. We set costs of goods sold to be equal to zero when missing for the GPOA and GMAR measures. For the ROE, we first use the income before extraordinary items and then the net income, based on availability.[3] We do not allow for stocks to have negative debt.[4] Because depreciation data is commonly missing in the merged CRSP/Compustat dataset, we allow depreciation to be missing in CFOA and ACC[5].

When calculating the working capital, we allow income taxes payable to be missing. This is allowed because income taxes payable usually is a small portion of the working capital, and many of the observations lacked it. We do not allow any other variables in the working capital to be missing. Therefore, we impute the missing accounting variables by using the same constructs as described in the merged CRSP/Compustat database. If the debt in current liabilities (DLC) is missing, we impute it by taking the sum of long-term debt due in one year (DD1) and notes payable (NP). After imputing DLC, we impute current liabilities (LCT) where it is missing by taking the sum of accounts payable (AP), debt in current liabilities (DLC), taxes payable (TXP), and other total current liabilities (LCO). Where the total liabilities (LT) is missing, we impute it by taking the sum of current liabilities (LCT), deferred taxes and investment tax credit (TXDITC), total long-term debt (DLTT), and other total liabilities (LO). If a firm lacks data about their total current assets (ACT), we impute it by taking the sum of cash and short-term investments (CHE),

[3] In the original paper, Asness et al. (2019) write that ROE is net income divided by book-equity, but in the appendix of the paper the abbreviation for income before extraordinary items (IB) is used. To be consistent, we use the abbreviations stated in the formulas of the original paper.

[4] We assume this to be a mistake in the data set. Less than 20 observations are removed

[5] See Appendix A

total inventories (INVT), total receivables (RECT), and other total current assets (ACO).

Because the growth measures are the five-year growth of all profitability measures except ACC, we make the same assumptions for the growth measures. We also divide all accounting variables by the common shares outstanding (CSHO) to measure the growth on a per-share basis. If a firm does not have data on common shares outstanding for one year, we use the data closest to that year available, prioritizing previous years over future years. For example, if a firm has common shares outstanding data for 1997 and 2001 but not in-between, we impute the CSHO value in 1998 and 1999 to be the same as the CSHO value in 1997 and the CSHO value in 2000 to be the same as the CSHO value in 2001. Further, we require firms to have at least one five-year growth value to be included.[6] To compute the residual profits as similar to Asness et al. (2019) as possible, we first compute the annualized risk-free rate using the monthly risk-free data available on AQR's database. We then subtract the passive income each firm would receive if it held its assets in risk-free securities from the year before each independent growth measure. Because the passive income needs observations from six years back and five years is our requirement, we allow residual income to be missing. See the appendix A for more details of how we compute the residual profits.

Because minority interest (MIBT) and preferred stock (PSTK) often are zero or a small portion of a firm's total debt, we set the missing values to be zero when calculating LEV. For the O-score, the annual consumer price index is downloaded from the US Bureau of Labour Statistics (2021).[7] The CPI from the year before the portfolio creation is used to avoid forward-looking bias. No variables are allowed to be missing for the computation, and the market equity from the month before is used. For Altman's Z-score, we set missing working capital and retained earnings values to be zero. Furthermore, we divide the firm's market equity component with the firm's book value of total debt, as in the original construct of Altman's Z-score (Altman, 1968). [8]

[6] If a firm has consecutive annual reports available, we require 6 years of Compustat data. If a firm has nonconsecutive data, but a five-year growth is available for one or more data points, we only include those.

[7] CPI for All Urban Consumers (CPI-U): All items less food and energy in U.S. city average, all urban consumers, seasonally adjusted.

[8] Asness et al. (2019) refers to Altman's original paper when constructing the formula. However, the market equity component in their paper is divided by the total assets. We do not find this practice in other papers and choose to use the definition formulated by Altman.

When constructing EVOL, we follow the restrictions made by Asness et al. (2019) and require 12 non-missing quarters. We use the standard deviation of quarterly ROE when available and the annual standard deviation when quarterly data is missing. The quarterly standard deviations are annualized to match the annual standard deviation. To merge the quarterly EVOL data with the monthly stock data, we set the first month of the quarter to be the month after the fiscal year ends and use this variable for the two next months. For example, if a firm's fiscal year ends in December, the quarter one data point is assigned the last trading day of January. The EVOL measure is then used February and March until quarter two starts.

To estimate the beta BAB, we follow the methodology described in Asness et al. (2019). The standard deviations of each stock and the market are the rolling one-year daily standard deviations. For the standard deviations, we require six months (120) days of trading data. To calculate the correlation, we use a rolling five-year window on the sum of three-day log returns. We require at least three years (750 days) of trading data for the correlations. To merge the daily data with the monthly data, we use the beta of the last trading day of each month.

3.3 Quality Score

We follow Asness et al. (2019) when calculating the quality score of any firm x at time t and first rank the firm on a relative basis compared to other firms at time t. EVOL is ranked in descending order. All other quality measures and combined measures are ranked in ascending order:

$$r_x = rank(x) \tag{3.1}$$

We then compute the z-scores of each quality measure by scaling the ranks to have zero cross-sectional mean and a cross-sectional standard deviation of one:

$$z(x) = \frac{[r_x - \bar{r}]}{\sigma(r_x)} \tag{3.2}$$

We compute the z-score of the profitability measures by taking the z-score of the profitability z-scores:

$$Profitability = z(z_{gpoa} + z_{roe} + z_{roa} + z_{cfoa} + z_{gmar} + z_{acc}) \tag{3.3}$$

We compute the z-score of the five-year growth measures by taking the z-score of the growth z-scores:

$$Growth = z(z_{\Delta gpoa} + z_{\Delta roe} + z_{\Delta roa} + z_{\Delta cfoa} + z_{\Delta gmar}) \tag{3.4}$$

We compute the z-score of the safety measures by taking the z-score of the safety z-scores:

$$Safety = z(z_{bab} + z_{lev} + z_{o} + z_{z} + z_{evol}) \tag{3.5}$$

To compute the quality score, we calculate the z-score of the combined z-scores:

$$Quality = z(Profitability + Growth + Safety) \tag{3.6}$$

We require every firm to have at least one z-score within each overarching factor, profitability, growth, and safety, to be included and given a quality score. This is an assumption we make that is not explicit in the original paper.

3.4 Portfolio Formation

As in the original paper, we do a double sort monthly based on size and quality to construct the QMJ factor. We start by separating the stocks into small and large portfolios, based on the NYSE market capital median as the size breakpoints. We then give each stock within both the small and large portfolios a quality rank as described in section 3.3 separately. The 30% highest (lowest) ranked stocks within the small and large portfolios are characterized as quality (junk) stocks. The portfolios are value-weighted, refreshed, and rebalanced every calendar month. The QMJ factor is long the average of the small quality and large quality portfolios, and short the average of small junk and large junk:

$$QMJ = \frac{1}{2}(Small\ Quality + Large\ Quality) - \frac{1}{2}(Small\ Junk + Large\ Junk) \tag{3.7}$$

We regress our replicated QMJ returns on the 3-factor, 4-factor, 5-factor, and 6-factor asset pricing models:

$$\mathrm{r}_t^e = \alpha + \beta^{MKT}MKT_t + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{RMW}RMW_t + \beta^{CMA}CMA_t + \beta^{UMD}UMD_t + \epsilon_t \tag{3.8}$$

The 3-factor model contains the first three right-hand side variables of equation 3.8. The 4-factor model includes UMD, in addition to the first three. The 5-factor model contains the first five right-hand side variables, and the 6-factor model includes all variables.

Our replicated and the original results of the QMJ, profitability, safety, and growth factors are presented in Table 3.1. Panel A shows the result of our factor regressions, while Panel B shows the original results presented in Tables 4 and 5 of the original paper.[9] For the purpose of this thesis, we consider the replication a success despite showing slightly different results. Both the profitability and growth factors show alphas close to the original, with statistically significant alphas in every regression. Safety generates positive alphas in every asset pricing model regression. In addition, the combined QMJ factor generates statistically significant alphas in every case. The magnitude of the alphas is slightly lower but still highly positive. The monthly 6-factor alpha for QMJ is 0.21%, compared to 0.33% in the original paper. As our goal is to replicate the quality proxy, the results are acceptable.

Overall, our replicated QMJ's factor loadings are similar to the original results. The loadings point in the same direction in every case except for UMD. Our QMJ exhibits a negative loading on UMD (momentum), whereas it is positive in the original paper. It is remarkable as all three factors that QMJ is comprised of have positive loadings

[9] Excess return, CAPM-alpha, 3-factor alpha, 4-factor alpha, and Sharpe-ratio from the original paper is calculated with returns from 07/1957 to 12/2016, while the 5-factor, 6-factor, and the single factor loading are calculated from 07/1963. The replicated QMJ is all calculated with results from 07/1957 to 12/2016.

on UMD. One possible explanation for the deviation is that our safety factor is not as prevalent in our QMJ as in the original paper. The monthly excess return of our safety factor is 0.17%, and the 6-factor alpha is 0.16%, compared to the original results 0.23% and 0.29% respectively. It can be attributed to a not-perfect replication. Furthermore, the factor data retrieved from Fama and French's website and the CRSP and merged CRSP/Compustat databases are frequently updated and may be subject to change, and our results are expected to deviate slightly. In general, our replicated QMJ is betting on low beta and book-to-market, big firms, aggressive, profitable, poorly performing stocks.

We make assumptions not explicit in Asness et al. (2019) that may account for the deviations in results. With a Sharpe ratio of 0.23, our safety factor is arguably the worst performing compared to the author's results. This is not surprising as the safety factor is the most complex factor to construct. It uses daily and monthly CRSP data, an unspecified CPI variable, and quarterly and annual CRSP/Compustat data. The merging method of all data sets may deviate slightly from how Asness et al. (2019) do it as it requires many assumptions to be made. Deviations in the merging procedure may explain part of the deviations in our results. Furthermore, the authors are unclear when describing how the variables are ranked. In general, the authors rank all variables in ascending order (Asness et al., 2019). However, ranking EVOL in ascending order is unintuitive because then one would bet on high ROE volatility. Furthermore, the formula they use for Altman's Z-score is not the same as in the original. We do not know whether it is a typo or if the formula is used as written. If our assumptions differ, this could explain part of the deviations observed.

The Sharpe ratio of our QMJ is 0.37, slightly lower than the original 0.47. This is likely due to our safety factor not being as strong, resulting in slightly more volatile or worse-performing stocks in the portfolio. While the factor loading of growth on HML is positive rather than negative, the QMJ factor loading on HML (book-to-market) is strongly negative. This means that our strategy is long cheap stocks, often referred to as value stocks. The negative loading on SMB (size) indicates that we are betting slightly more on large stocks. Betting on large, cheap stocks is consistent with the findings of Novy-Marx (2013). This is further evidence that we can use the constructed QMJ factor as a quality proxy.

Table 3.1: QMJ Replication

This table shows the portfolio excess returns of the QMJ, profitability, safety and growth portfolios, and their factor loadings. Panel A shows the replication, while Panel B shows the results of Asness et al. (2019). The sample period runs from June 1950 to December 2016, with first portfolio return July 1957. The data is downloaded from CRSP and Compustat. The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality, refreshed and re-balanced monthly to sustain the value weights. The size breakpoints are constructed using the median NYSE market equity. After sorting on size, the portfolios are sorted on quality. The QMJ factor is the average return on the two high-quality portfolios minus the average return on the low quality portfolios. The portfolio returns of profitability, growth, and safety are constructed similarly. The factor returns for size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), momentum (UMD) and the market (MKT) are downloaded from Kenneth French's data library (2021). The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported on a monthly basis, and the t-statistics in parenthesis are displayed under the coefficient estimates. Sharpe ratios are annualized.

	QMJ	Profitability	Growth	Safety	QMJ	Profitability	Growth	Safety
Excess Return	0.25	0.18	0.17	0.19	0.29	0.25	0.23	0.17
	(2.74)	(2.29)	(1.67)	(3.04)	(3.62)	(3.69)	(2.44)	(2.46)
CAPM-alpha	0.36	0.25	0.32	0.21	0.39	0.32	0.40	0.16
	(4.35)	(3.25)	(3.76)	(3.41)	(5.43)	(4.75)	(5.52)	(2.28)
3-factor alpha	0.49	0.41	0.42	0.25	0.51	0.40	0.52	0.28
	(6.37)	(5.89)	(5.34)	(4.00)	(8.90)	(6.97)	(9.06)	(5.17)
4-factor alpha	0.37	0.35	0.33	0.16	0.60	0.50	0.51	0.46
	(4.91)	(4.95)	(4.19)	(2.66)	(9.95)	(8.32)	(8.39)	(8.29)
5-factor alpha	0.29	0.23	0.22	0.22	0.38	0.29	0.38	0.30
	(4.67)	(4.03)	(3.13)	(3.62)	(7.71)	(6.85)	(5.75)	(6.60)
6-factor alpha	0.21	0.20	0.16	0.15	0.33	0.28	0.29	0.27
	(3.48)	(3.41)	(2.35)	(2.51)	(6.81)	(6.54)	(4.49)	(5.85)
MKT	-0.17	-0.11	-0.21	-0.06	-0.17	-0.08	-0.28	-0.05
	(-11.17)	(-7.42)	(-12.28)	(-4.43)	(-14.07)	(-7.72)	(-17.60)	(-4.47)
SMB	-0.07	-0.07	-0.20	0.08	-0.11	-0.07	-0.19	0.03
	(-3.33)	(-3.39)	(-8.27)	(4.28)	(-6.51)	(-4.57)	(-8.89)	(1.83)
HML	-0.17	-0.27	-0.16	0.04	-0.26	-0.29	-0.19	-0.26
	(-5.66)	(-9.53)	(-4.62)	(1.53)	(-10.85)	(-13.80)	(-6.26)	(-11.88)
CMA	-0.05	-0.01	0.14	-0.24	-0.05	0.09	0.04	-0.36
	(-1.27)	(-0.24)	(2.85)	(-5.81)	(-1.39)	(3.04)	(0.97)	(-11.46)
RMW	0.54	0.49	0.46	0.18	0.55	0.58	0.32	0.33
	(18.84)	(17.82)	(13.86)	(6.37)	(24.07)	(28.37)	(10.67)	(15.70)
UMD	-0.17	0.05	0.08	0.10	0.07	0.01	0.13	0.05
	(-5.66)	(3.54)	(4.63)	(7.00)	(5.68)	(1.25)	(8.87)	(4.37)
Sharpe Ratio	0.37	0.31	0.23	0.42	0.47	0.48	0.32	0.32

3.5 Recessions and Investor Herding

In order to answer our research question, we use the Thomson/Refinitiv quarterly 13-F Filings from December 1998 to December 2019. The time span is shorter, due to data availability. The Thomson 13f database is where Choi and Sias (2009) find evidence of institutional investor herding (Choi and Sias, 2009). It is reasonable to assume that evidence of a potential flight to quality should be found using data of the same origin.

We do not differentiate between the different funds. However, we only include funds that hold common equity in NYSE, Nasdaq, and AMEX, and only look at the common equity spectrum. To assign the holdings to quality and junk stocks, we use the quality portfolios from the replicated QMJ factor. Not all stocks are eligible for a quality score as the stocks may not fulfill the criteria mentioned in section 3.4. We choose to keep all common stocks regardless as they give a clearer picture of how the institutional investor reallocates its funds within the equity market. The stocks are separated into four different subcategories, depending on their quality ranking. All stocks that are eligible for a quality score are assigned the score received in the monthly QMJ portfolios described in section 3.4. The stocks that do not have a quality score remain *unqualified*. The quality ranking is independent of the institutional investor portfolios.

The portfolio size, in USD, of each institutional investor n is calculated each quarter by taking the sum of all shares i held at the end of the quarter t multiplied by the price of the stock [10] at the end of the quarter:

$$PortSize_{n,t} = \sum Shares_{i,t} * Price_{i,t} \tag{3.9}$$

We then calculate the individual positions each investor holds in stock i at quarter t by dividing the position size by the total portfolio size of the investor.

$$Position_{n,i,t} = \frac{Shares_{i,t} * Price_{i,t}}{PortSize_{n,t}} \tag{3.10}$$

To understand how large part of the stock market comprises of quality stocks, we create a variable $MCap_{Q,t}$ that is the sum of all quality firms' market caps divided by the total market cap of the NYSE, AMEX, and NASDAQ stocks at any quarter t.

$$MCap_{Q,t} = \frac{\sum MarketCap_{q,t}}{TotalMarketCap_t} \tag{3.11}$$

To know how large share institutional investors invest in quality firms at any quarter, we create a quality ratio QR that is the sum of an investor's positions within stocks that are classified as quality stocks, at quarter t. In other words, the QR is the share of an

[10]The prices for the calculations are taken from Center for Research on Security Prices (CRSP). This is to get compararable measurements, as some prices are missing.

investor's portfolio size that is allocated to quality.

$$QR_{n,q,t} = \sum Position_{n,q,t} \tag{3.12}$$

Likewise, we create a variable that calculates the share of an investor's portfolio that is invested in firms classified as junk, at quarter *t*.

$$JR_{n,j,t} = \sum Position_{n,j,t} \tag{3.13}$$

We then create ΔQR and ΔJR which measure the changes in each investor's quality and junk ratios at quarter *t* and quarter *t-1*.

$$\Delta QR_{n,q,t} = QR_{n,q,t} - QR_{n,q,t-1} \tag{3.14}$$

$$\Delta JR_{n,j,t} = JR_{n,j,t} - JR_{n,j,t-1} \tag{3.15}$$

To test whether investors are actively betting on quality stocks as part of their investment strategy or whether they invest in quality firms as part of diversification strategies, we adjust the investor's quality ratio by subtracting the market share of quality stocks. The same is done for the junk ratio.

$$AdjustedQR_{n,q,t} = QR_{n,q,t} - MCap_{q,t} \tag{3.16}$$

$$AdjustedJR_{n,j,t} = JR_{n,j,t} - MCap_{j,t} \tag{3.17}$$

In other words, to adjust for diversification effects by measuring the investor's exposure to quality on top of the share of quality stocks in the market. The same applies to the adjusted junk ratio. The intuition behind this metric is that if quality firms account for 5% of the market at any point in time *t*, a 5% exposure of investors in quality firms at time t is rather the result of deliberate diversification than a bet on quality. It allows us to measure the active quality (junk) exposure of any investor at any quarter.

We use NBER's definition of recession and obtain recession data from NBER's website (NBER, 2021). It is the same definition Asness et al. (2019) use when they look at how the QMJ strategy performs during recessions. We conduct the same analysis and the sample data for this runs from January 1957 to December 2020 and includes ten recession periods. The last recession occurs in 2020, after the publishing of the original paper. Thus, our results will differ slightly. We assign the dates a recession dummy variable where any particular month is either a recession (where the dummy is equal to 1) or an expansion (non-recession).

As the 13f data is quarterly format from 1998 to 2019 due to data availability and we use the recession data between 1998 and 2019. In this sub-sample, we include two recessions, from March 2001 to November 2001 and from December 2007 to June 2009. If any of a particular quarter's months are in the recession time frame, we assign a recession dummy at the end of the quarter. For example, if the recession ends in November 2001, we assign the recession dummy to the end of December 2001. This is reasonable to do, as the 13f forms contain data of the holdings at the end of a particular quarter and reflect the behavior of the institutional investors throughout the entire quarter, including recession months.

For robustness, we test whether the results obtained are consistent during other market downturns in addition to recessions. We replace the recession dummy with a dummy that is equal to one when the past quarterly returns are negative. For example, if the market return from March 31st to June 30th is negative, we assign a recession dummy at the end of June. This allows us to test another definition of "market downturn" and whether the quality outperforms also in these periods.

4 Empirical Analysis

In this section, we conduct an empirical analysis to answer whether there is a *flight to quality* within the US equity market during recessions. Firstly the performance of the QMJ factor during recessions and high volatility environment is analyzed. We separate and compare the returns of quality and junk stocks, to better understand whether the QMJ returns come from going long quality or shorting junk. Secondly, we look at the investor bets on quality and junk. We present descriptive statistics of the institutional investors' holdings. The stocks of the institutional investor portfolios are assigned quality scores and their portfolios are analyzed. How much each investor invest in quality and junk stocks is then computed and analyzed with the market share of quality and junk stocks. Thirdly, we analyze the changes in quality and junk ratios described in equations 3.14 and 3.15. We present four regression tables showing results of the change in investors' quality ratio, junk ratio, QMJ ratio, and the change in quality ratios adjusted for their respective market shares. The goal is to test whether investors flee to quality and move out from junk during recessions.

4.1 QMJ during Recessions

To investigate the performance of the QMJ factor in recessions, the paper follows a slightly modified methodology to that of Asness et al. (2019). The replicated QMJ returns used cover July 1957 until May 2020, whereas the original paper only looks until December 2016. This allows us to capture the most recent recession period in 2020. Recession periods are the NBER recessions, as described in section 3.5. All non-recession months are defined as expansion months. Severe bull and bear markets are defined as when the rolling 12-month volatility is above or below 15%. Low and high volatility periods are extracted using the one-month standard deviation of the daily returns of the value-weighted CRSP index. The sample is then split into the top and bottom 30%, which signifies the low and high volatility periods. Spike up and down in volatility is determined based on the one-month change in market volatility, split into the top and bottom 30%.

Testing the QMJ factor's performance during different market behaviors shows evidence of the "flight to quality" stipulated by Asness et al. (2019). This is puzzling from a risk-based point of view, as the alpha increases during times of high volatility. Even when controlling for the conventional asset pricing risk factors, the alphas are significant. One would expect strategies that perform well during market distress to be higher priced. The over-performance suggests that investors, in addition, move to safer equities and towards a QMJ strategy, further motivating this thesis.

Table 4.1: QMJ during Recessions and High Volatility Environment

This table shows the portfolio excess returns and factor loading's of the QMJ factor The sample period runs from June 1950 to December 2016, with first portfolio return July 1957. Data is downloaded through CRSP and Compustat, and contains stocks from the US. The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality, refreshed and re-balanced monthly to sustain the value weights. Recession periods are defined in accordance with NBER (2021). Severe bull and bear markets are defined as when the rolling 12-month volatility is above or below 15%. Low and high volatilises are the top and bottom 30% periods based on the one-month standard deviation of the daily returns of the value-weighted CRSP index. Spike up and down in volatility is determined based on the one-month change in market volatility, split into the top and bottom 30%. The factor returns for size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), momentum (UMD) and the market (MKT) are downloaded from Kenneth French's data libraryFrench, K. (2021). The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported monthly, and the t-statistics are displayed on the right-hand side.

	Return				t-statistics				
	Excess Return	CAPM	3-Factor	4-Factor	Excess Return	CAPM	3-Factor	4-Factor	Nr. Months
All Periods	0.26	0.38	0.47	0.36	3.16	5.10	7.13	5.49	755
Recession	0.60	0.44	0.54	0.49	1.20	1.68	2.42	2.32	113
Expansion	0.20	0.36	0.46	0.34	2.48	4.77	6.72	5.03	642
Severe Bear Market	0.96	-0.18	-0.33	-0.06	1.27	-0.26	-0.52	-0.09	30
Severe Bull Market	-0.14	-0.07	0.17	0.13	-0.58	-0.26	0.66	0.50	61
Low Volatility	-0.20	-0.14	0.24	0.10	-1.21	-0.72	1.63	0.62	91
High Volatility	0.66	0.48	0.32	0.39	1.90	1.79	1.29	1.60	91
Spike up in Volatility	0.20	0.64	0.09	0.08	3.31	2.42	0.42	0.36	91
Spike down in Volatility	-0.30	0.16	0.46	0.35	-1.32	0.67	2.03	1.49	91

To better understand the dynamics of the QMJ factor during recessions, we look into how quality and junk perform separately during recessions and high volatility environment. The motivation behind this is to see if the QMJ returns stem from going long quality stocks or shorting junk stocks. If a large part of the return comes from buying quality stocks during recessions, it could give an indication that investors herd to quality. It can also provide evidence for a flight from junk stocks.

Table 4.2 shows that the high return obtained from the QMJ factor during recessions, high volatility, spike up in volatility, and severe bear markets stem from the shorted junk stocks performing significantly worse than the quality stocks. In other words, the quality stocks exhibit a negative return during these periods, but the return overall becomes positive because the junk stocks have an even lower return. The negative returns can be attributed to investors leaving the equity markets in general. However, this suggests that the demand for quality stocks is higher than for junk stocks in relative terms, implying a

Table 4.2: Quality and Junk during Recessions and High Volatility Environment

This table shows the portfolio excess returns and factor loading's of quality and junk portfolio.The sample period runs from June 1950 to December 2016, with first portfolio return July 1957. Data is downloaded through CRSP and Compustat, and contains stocks from the US. Quality consists of both large and small high-quality stocks, while junk consists of large and small low-quality stocks. The portfolios are refreshed and re-balanced monthly to sustain the value weights. Recession periods are defined in accordance with NBER (2021). Severe bull and bear markets are defined as when the rolling 12-month volatility is above or below 15%. Low and high volatilises are the top and bottom 30% periods based on the one-month standard deviation of the daily returns of the value-weighted CRSP index. Spike up and down in volatility is determined based on the one-month change in market volatility, split into the top and bottom 30%. The factor returns for size (SMB), book-to-market (HML), investment (CMA), profitability (RMW), momentum (UMD) and the market (MKT) are downloaded from Kenneth French's data libraryFrench, K. (2021). The excess returns are over the U.S. monthly T-bill rate. Alphas and the excess returns are reported monthly. T-statistics is reported in parenthesis under the coefficient estimates.

	Quality				Junk				
	Excess Return	CAPM	3-Factor	4-Factor	Excess Return	CAPM	3-Factor	4-Factor	Nr. Months
All Periods	0.10	-0.45	-0.47	-0.50	-0.16	-0.83	-0.94	-0.86	755
	(0.57)	(-8.39)	(-11.04)	(-11.49)	(-0.73)	(-9.69)	(-16.02)	(-14.59)	
Recession	-1.38	-0.69	-0.75	-0.78	-1.98	-1.13	-1.29	-1.27	113
	(-2.03)	(-3.73)	(-5.39)	(-5.90)	(-2.28)	(-3.42)	(-5.65)	(-5.58)	
Expansion	0.36	-0.39	-0.41	-0.42	0.16	-0.75	-0.86	-0.76	642
	(2.16)	(-7.18)	(-9.30)	(-9.38)	(0.77)	(-9.05)	(-15.42)	(-13.77)	
Severe Bear Market	-5.43	-1.41	-1.21	-0.81	-6.39	-1.23	-0.88	-0.75	30
	(-3.54)	(-2.81)	(-3.50)	(-2.93)	(-3.10)	(-1.31)	(-1.41)	(-1.13)	
Severe Bull Market	1.90	-0.03	-0.22	-0.23	2.03	0.04	-0.38	-0.36	61
	(4.56)	(-0.15)	(-1.44)	(-1.52)	(4.47)	(0.15)	(-2.18)	(-2.02)	
Low Volatility	1.23	-0.18	-0.26	-0.32	1.43	-0.04	-0.51	-0.42	91
	(4.23)	(-1.60)	(-3.71)	(-4.28)	(4.22)	(-0.20)	(-4.09)	(-3.17)	
High Volatility	-1.64	-1.08	-0.81	-0.79	-2.30	-1.56	-1.13	-1.18	91
	(-2.21)	(-5.03)	(-5.26)	(-5.09)	(-2.29)	(-4.14)	(-4.28)	(-4.46)	
Spike up in Volatility	-2.54	-1.02	-0.45	-0.45	-3.53	-1.66	-0.55	-0.53	91
	(-3.59)	(-5.00)	(-3.05)	(-3.03)	(-3.88)	(-4.48)	(-2.33)	(-2.31)	
Spike down in Volatility	1.79	-0.12	-0.26	-0.22	2.09	-0.28	-0.72	-0.56	91
	(4.44)	(-0.71)	(-1.97)	(-1.58)	(3.99)	(-1.04)	(-4.10)	(-3.22)	

flight to quality. Another potential explanation is that the returns can be attributed to a flight from junk.

4.2 Investor bets on Quality

In Table 4.3 we report the descriptive statistics of the data used in the empirical analysis. The data-set consists of the institutional holdings combined with the quality (or junk) definition created in the previous section. All periods show the mean, median, and standard deviation of our quarterly data from December 1998 to December 2019. Recessions indicate NBER recession quarters as described in section 3.5, and expansions are every other quarter. In total, we have ten recessions and 71 expansion quarters. The quality and junk ratio show the relative weight of each institutional investor's portfolio that is allocated in quality and junk stocks. The mean and median quality ratios during recessions are 39% and 40% respectively, slightly higher than the recorded 35% during expansions. The mean junk ratio during recessions is one percentage point lower than the recorded 13% during expansions. This suggests that investors, on average, invest more in quality stocks during recessions. On the other hand, investors do not seem to remain invested in junk stocks.

The delta quality ratio shows the change in quality ratio from quarter *t-1* to quarter *t*. It is slightly higher during recessions, suggesting that investors increase their exposure in quality during recessions. The description table also includes the mean ratio of a pruned quality ratio, which only includes investors that do not hold more than 30% of their portfolio in one individual stock and have a quality ratio in the bottom 80%. This measure intends to look at investors that do not invest heavily in quality stocks and specifically see their behaviour during recessions. Moreover, this ratio removes the investors holding one or a few larger holdings that that drive their quality ratio.

The portfolio size shows the dollar value of the investors' holdings in common equity. In general, the portfolio size of institutional investors is larger during expansions than recessions. This could be a consequence of general market declines during recessions and the withdrawal of funds by investors. The median portfolio size is USD 285.79M, whereas the mean portfolio size is USD 4.02B. The results indicate that most funds are smaller institutional investors, and the mean holdings are lifted by a few large investors. The quarterly returns report the quarterly market return and have a negative correlation with recessions. We document 26 quarters with negative returns, which is higher than the number of official NBER recessions.

The market value of quality and junk stocks show the respective portion of the market cap the quality and junk stocks account for in relative terms to the entire NYSE, AMEX, NASDAQ market value. The market value of quality stocks is slightly higher, and the market value of junk stocks is slightly lower during recessions compared to expansions. The mean quality ratio of institutional investors is 35% compared to the relative market value of quality stocks that is 28%. The results suggest that institutional investors are generally more invested in quality than the relative market value of quality, implying that investors bet more on quality than a general diversification strategy would presume. This is also true during recessions, as the average quality ratio increases from 35% to 39%, whereas the market value of quality stocks increases to 30%. The average quality ratio of pruned investors is 26% and 28% during expansion and recessions, respectively. Compared to the market value of quality stocks, these results suggest that most investors hold quality stocks as part of a general diversification strategy rather than actively betting on quality.

For all volatility measures, the volatility is recorded as the annualized past three months volatility. The volatility of QMJ is the volatility of the QMJ strategy, the volatility of quality and junk stocks are the annualized value-weighted three-month volatility of the quality and junk stock returns. All volatility measures increase during recessions. Quality stocks and the QMJ strategy exhibit lower volatility than junk stocks and the market during recessions. The volatility of junk stocks is the highest overall, during recessions, and during expansions. The fact that the mean volatility of junk stocks jumps from 13% during expansions to 28% during recessions suggests that junk stocks are sensitive to market downturns. The QMJ strategy shows the lowest volatility during all periods. The evidence suggests that there is a *flight to quality* but not from junk among institutional investors. However, this seems to be largely driven by investors that are already betting heavily on quality. Quality stocks and the QMJ strategy are less volatile and risky.

Table 4.3: Descriptive Statistics

This table shows descriptive statistics of the quarterly data of institutional investors' holdings, quality, and junk stocks from December 1998 to December 2019.
The market share of quality and junk stocks and all volatility measures are computed using data from CRSP. Investor holdings, quality, and junk ratios, and portfolio size are computed using Thomson 13f filings. Portfolio size is measured in USD. The left column reports the time-series average, median, and standard deviation of all quarters over the time sample. The recessions column shows only results during recessions. The expansion column shows data from every quarter that is not a recession.

	All Periods			Recessions			Expansions		
	Mean	St. Dev	Median	Mean	St. Dev	Median	Mean	St. Dev	Median
Quality Ratio	0.35	0.13	0.35	0.39	0.13	0.40	0.35	0.13	0.35
Delta Quality Ratio	0.01	0.10	0.01	0.02	0.10	0.03	0.01	0.10	0.01
Junk Ratio	0.13	0.07	0.12	0.12	0.07	0.12	0.13	0.08	0.12
Quality Ratio Pruned	0.28	0.10	0.30	0.32	0.10	0.33	0.28	0.10	0.29
Quarterly Returns	0.02	0.09	0.04	-0.06	0.12	-0.09	0.03	0.07	0.04
Market Share Quality Stocks	0.28	0.03	0.27	0.30	0.03	0.30	0.28	0.03	0.27
Market Share Junk Stocks	0.11	0.04	0.10	0.11	0.03	0.11	0.12	0.04	0.10
Portfolio Size	4.02B	32.68B	285.79M	3.08B	18.52B	226.20M	4.13B	33.96B	293.26M
Volatility Market	0.12	0.07	0.11	0.21	0.09	0.20	0.11	0.06	0.09
Volatility QMJ	0.07	0.06	0.05	0.12	0.08	0.08	0.07	0.05	0.05
Volatility Quality Stocks	0.11	0.07	0.09	0.19	0.08	0.18	0.10	0.06	0.08
Volatility Junk Stocks	0.15	0.10	0.13	0.28	0.12	0.26	0.13	0.09	0.10
Nr. of Quality Stocks	642.68	132.15	606.00	654.60	140.87	591.00	641.09	131.86	609.00
Percentage Quality Stocks	0.08	0.02	0.08	0.08	0.02	0.07	0.08	0.02	0.08
Small Firms	701								
Large Firms	493								
Recession Periods	10								
Negative Return Periods	26								

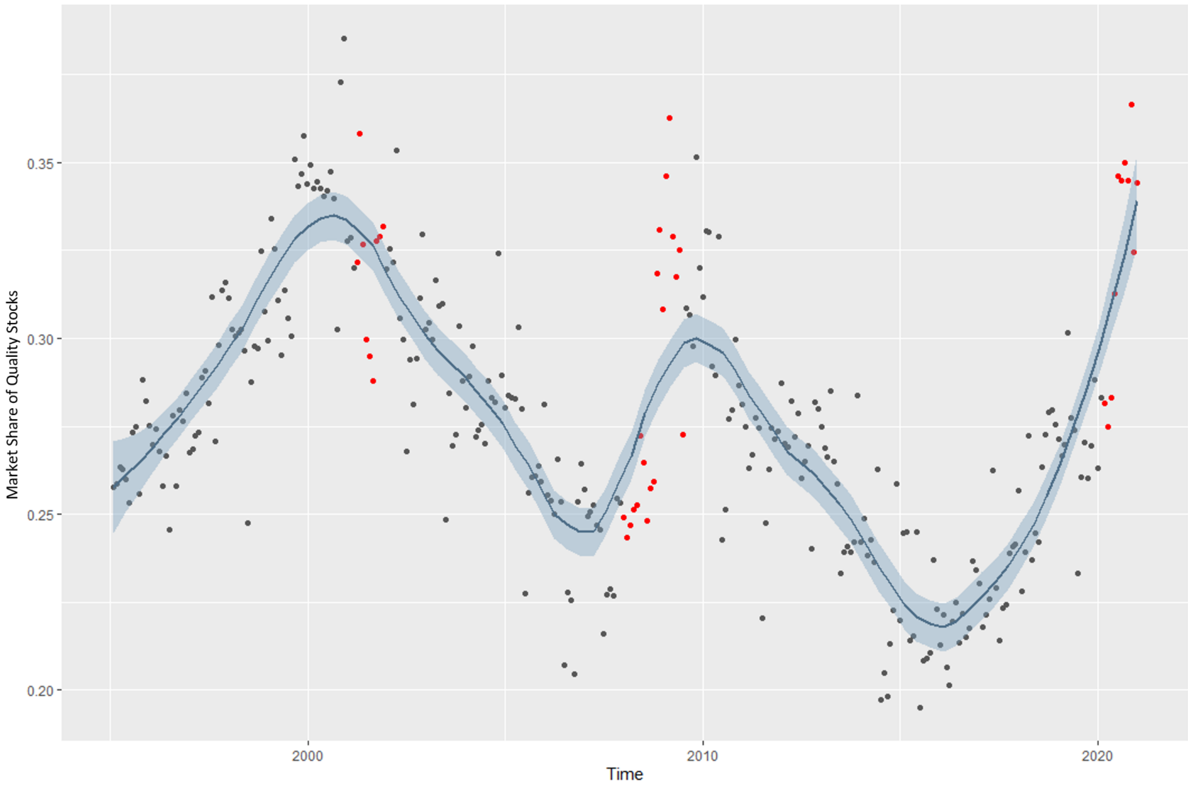
Figure 4.1 shows the value of the quality stocks relative to the total NYSE, AMEX, NASDAQ equity markets. The plot uses a few months out-of-the-sample to better graph the trendline. The trendline indicates that quality stocks become a larger share of the market as the market goes down. Although the value of quality stocks seems to decrease

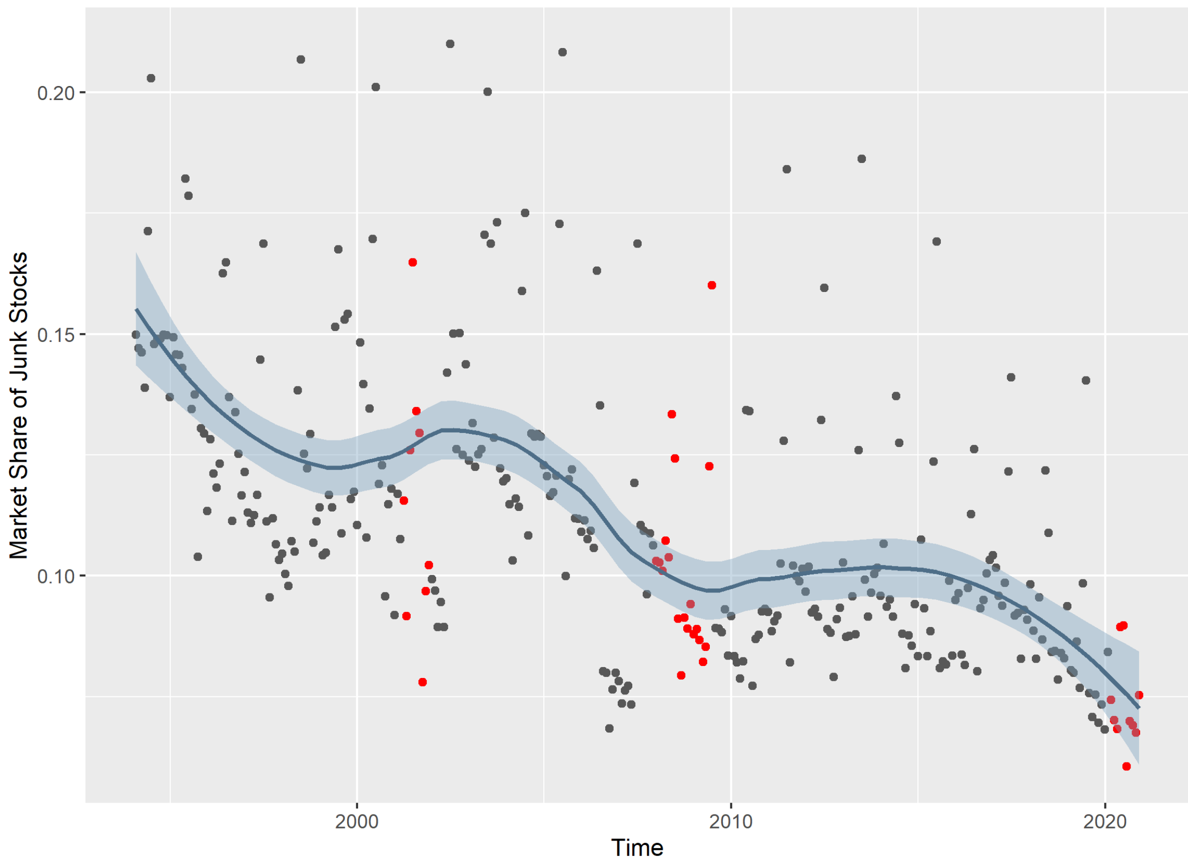
in the recession 2001, the months preceding the recession in 2001 are tainted by the dot com crash. Quality stocks became a larger share of the total market toward the 2007-2009 recession and stayed high a few years after. The plot shows that this is also the case during the Covid-19 pandemic.

Figure 4.2 is a plot of the average quality ratio among institutional investors over time. The plot shows that the quality ratio is dispersed and seems to be random. However, the plot suggests that the highest quality ratio values are observed around the dot com crash in 2000 and the financial crisis 2007-2009. As the first plot in figure 4.2 shows no clear trend following the pattern observed in 4.1, one can infer that investors must actively bet differently during recessions and expansions. Following the financial crisis in 2007-2009, both the average quality ratio and market share of quality stocks are relatively high. This may not be a coincidence as the quality ratio is measured as a relative holding ratio. This gives rise to a mechanical explanation of quality betting, suggesting that the *flight to quality* could be involuntary. Looking at the junk ratio over time in 4.2, one can see a positive trend in the early 2000s, but after the financial crisis, the ratio flattens. As the market share of junk stocks shows a negative trend, a flat junk ratio implies that investors make active bets in junk stocks. It can be inferred because the mechanical market share adjustments would naturally imply a decline in junk ratio.

Figure 4.3 shows the mean quality and junk ratios subtracted by the market shares of the respective stocks, as described in equations 4.4 and 3.17. The plots indicate whether, and to what extent, institutional investors on average actively bet on quality and junk stocks. The overall trend for quality stocks is scattered and relatively flat. However, institutional investors invest more in quality stocks than their relative market share would suggest. This is observed by the general trend line staying above zero. The second plot shows that the average bet on junk has an upward trend. This implies that investors bet more in junk stocks in recent years than historically. The results are robust to recessions and after adjusting for the market share of junk stocks, suggesting that the behavior is driven by other factors. The trend confirms the plots observed in figures 3.11 and 4.2, suggesting that the active bets in junk stocks are not explained by mechanical adjustments of market share.

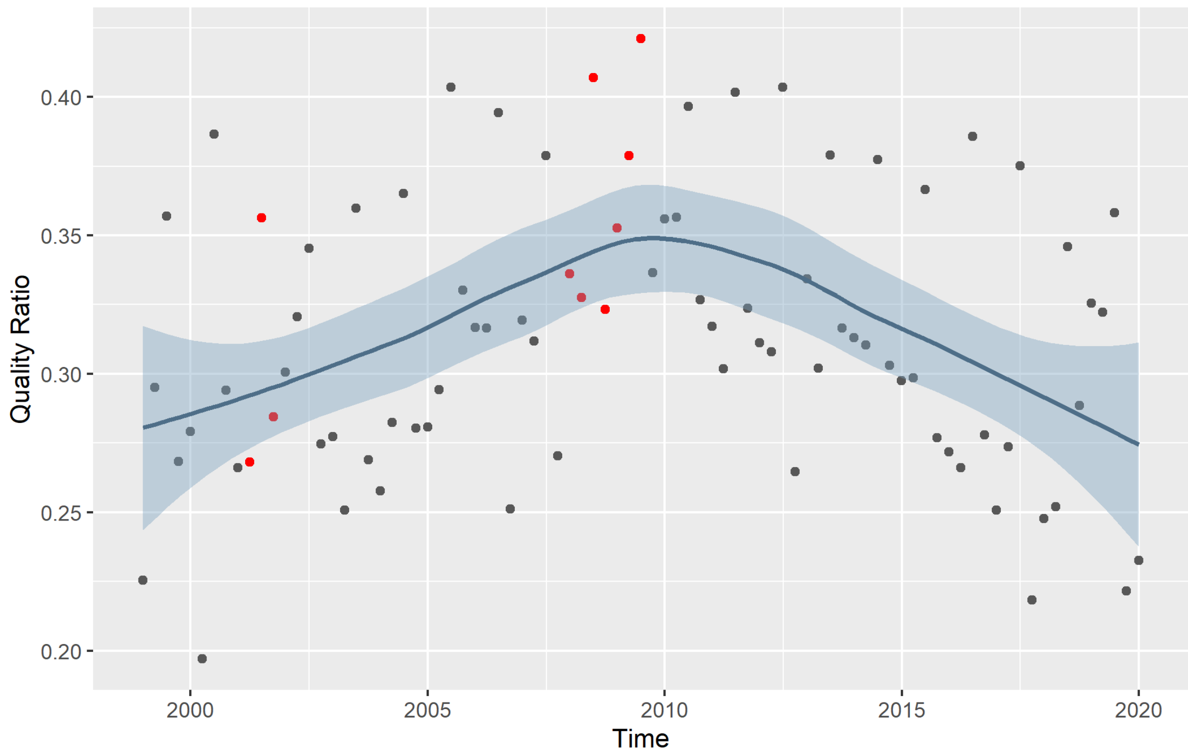
Figure 4.1: Market Share of Quality and Junk Stocks Over Time

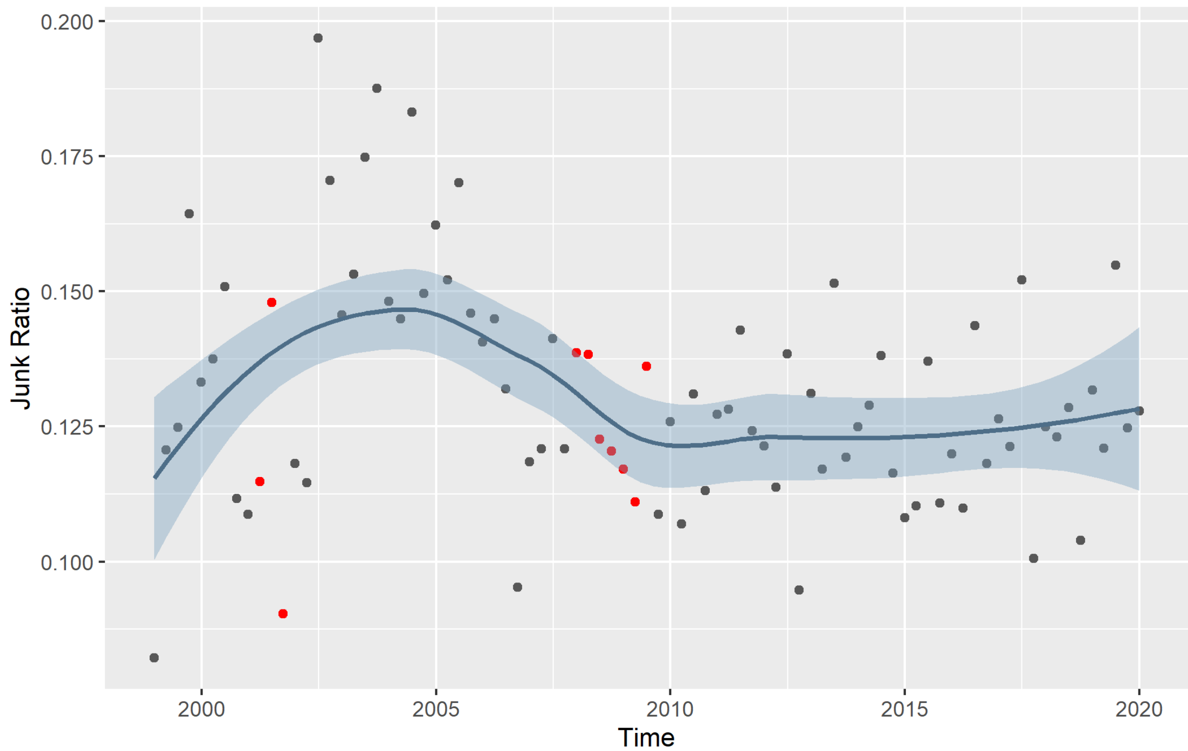




The first plot shows the monthly mean market share of all quality stocks, and the second plot shows the mean market share of all junk stocks. The market shares are computed as a relative measure to the total market. The time sample is from January 1994 to December 2020. The dots represent the mean market share at each particular month. The blue dots represent expansion months, and the red dots represent the NBER recession months. The line shows a trend curve that is a smoothed rolling regression of the mean values observed as dots.

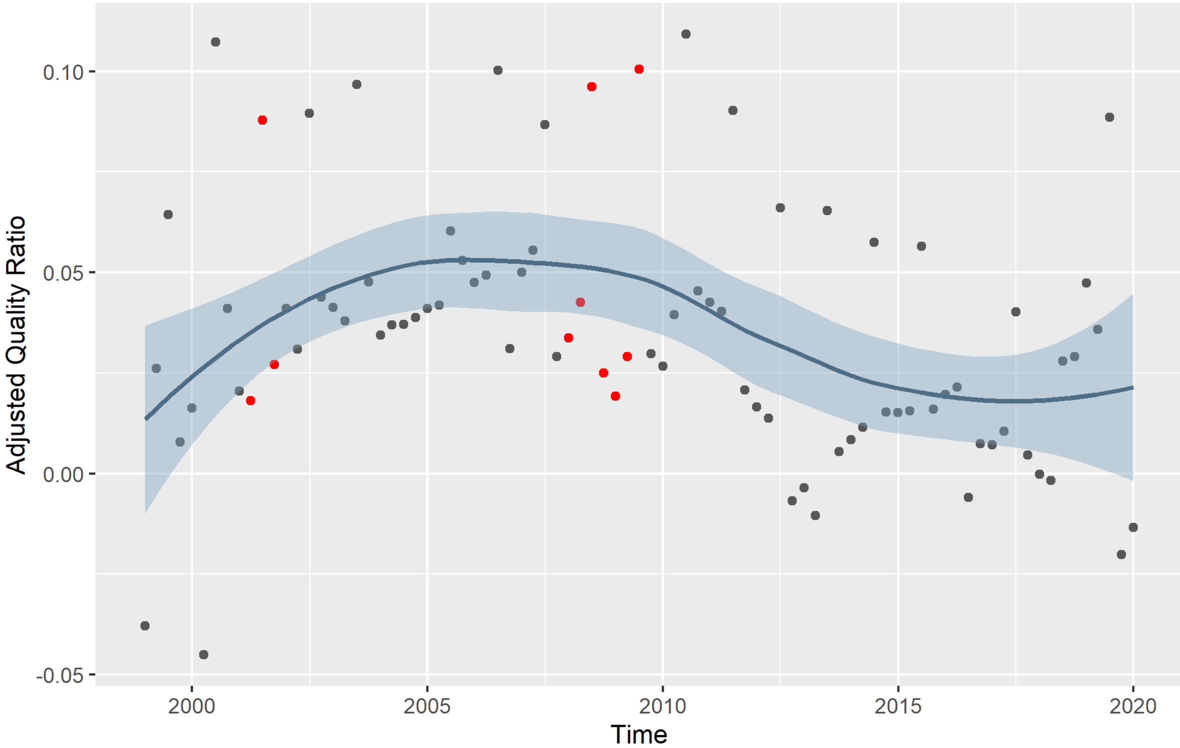
Figure 4.2: Mean Quality and Junk Ratio of the Institutional Investors Over Time

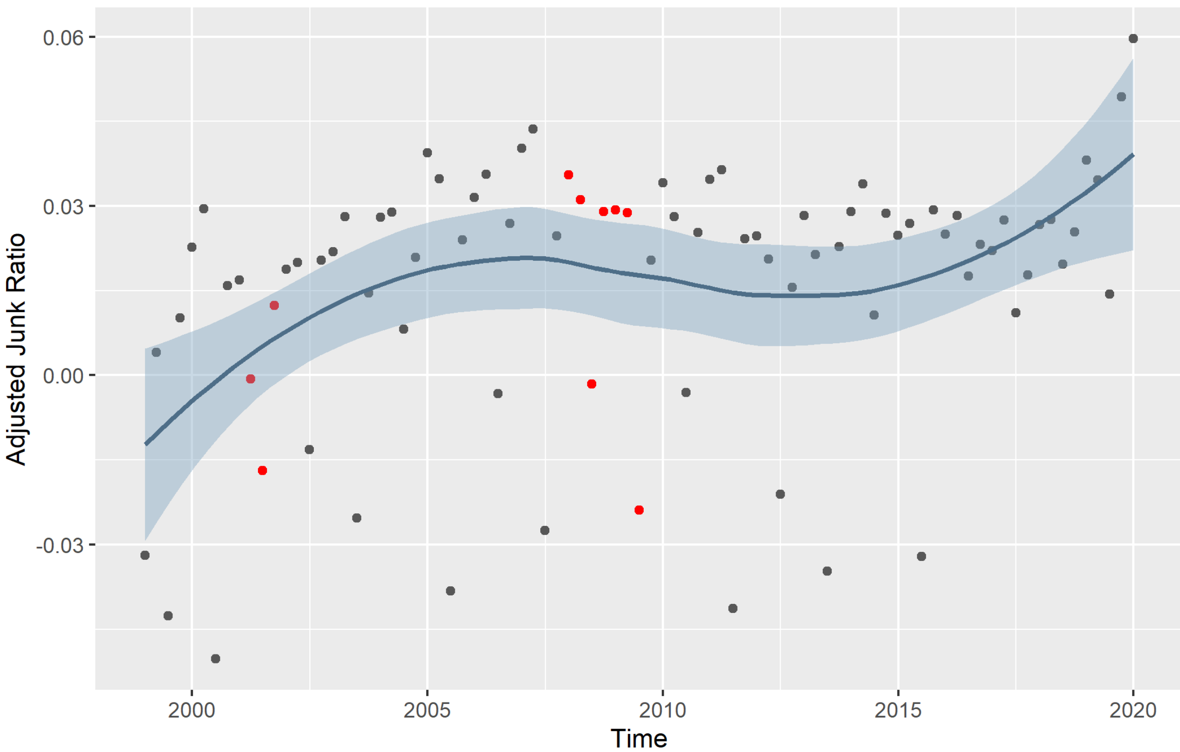




The first plot shows the monthly mean quality ratio of institutional investors over time. The second plot shows the mean junk ratio of institutional investors over time. The time sample is from December 1998 to December 2019. The dots represent the mean quality and junk ratio at each quarter. The blue dots represent expansion quarters, and the red dots represent quarters where at least one of the months is an NBER recession month. The line shows a trend curve that is a smoothed rolling regression of the mean values observed as dots.

Figure 4.3: Quality and Junk Ratios Adjusted for Their Market Shares





The first plot shows the monthly mean quality ratio subtracted from the monthly mean market share of quality stocks. The second plot shows the monthly mean junk ratio subtracted from the monthly mean market share of junk stocks. The time sample is from January 1994 to December 2020. The dots represent the mean adjusted ratio for each particular month. The blue dots represent expansion months, and the red dots represent the NBER recession months. The line shows a trend curve that is a smoothed rolling regression of the mean values observed as dots.

4.3 Deliberate or Involuntary?

In this section, we further investigate the flight to quality through several regressions. We want to test whether investors move into quality stocks and out of junk stocks during recessions. Firstly, we measure the impact recessions have on investors' change in quality and junk ratios[11]. The goal is to obtain the magnitude and direction a recession period impacts the changes. Recessions involve a broad decline in economic activity that lasts for several consecutive months (NBER, 2021). Hence, a recession coincides with confounding variables that also may impact investors' decision-making. We control for time-varying variables like market returns, market share of quality and junk stocks relative to the total market, volatility of the market, and volatility of quality and junk stocks. Further, we control for the size of the investors to compare whether smaller investors invest differently from larger investors. Secondly, we do the same regression using a QMJ ratio to determine whether the change in the spread between quality ratio and junk ratio can be explained by recessions or the other independent variables. Lastly, we discuss the implications of our findings.

4.3.1 Quality Ratio

We want to test whether the change in quality ratio (QR) among institutional investors increase during recessions. Therefore, we distinguish between recession periods and non-recession periods and regress the delta quality ratio created in equation 3.14 on time-varying variables and a cross-sectional variable. The change in quality ratio of each institutional investor n at time t is our dependent variable. The data is on a quarterly basis and *t-1* indicates the previous quarter. We include market share of quality stocks as described in equation 3.11 to test whether the QR can be partly explained by the market cap of quality stocks. For the cross-sectional variability, we rank the portfolio size of each institutional investor and test whether the size of portfolio affect the change in quality ratio. We control for the standard deviation of the market, QMJ strategy, and quality stocks, by including a value-weighted annualized three-month standard deviation of each variable. Lastly, distinguish between recessions and expansions by including a dummy variable as described in section 3.5 and multiplying it with all variables except portfolio

[11] Details on how quality and junk ratios are constructed can be found in section3.5

size and market returns:

$$\Delta QR_{n,t} = \alpha + \beta_1 Ret_t + \beta_2 Ret_{t-1} + \beta_3 Port_{n,t} + \beta_4 MC_{Q,t} + \beta_5 SD_{Q,t} + \beta_6 SD_{M,t} + \beta_7 SD_{QMJ,t}$$
$$+ \beta_8 REC_t + \beta_9 REC_t * SD_{QMJ,t} + \beta_{10} REC_t * MC_{Q,t} + \beta_{11} REC_t * SD_{Q,t} + \beta_{12} REC_t * SD_{M,t} + \epsilon_t \tag{4.1}$$

Where $\Delta QR_{n,t}$ is the change in quality ratio of the institutional investor n at time t, Ret_t and Ret_{t-1} are the quarterly market returns and previous quarterly market returns respectively. $Port_{n,t}$ is the portfolio size of the investor n at time t, relative to other investor's portfolio sizes[12]. $MC_{Q,t}$ is the market share of all quality stocks, relative to the total market, at time t. $SD_{M,t}$ is the annualized three-month standard deviations of the market, $SD_{Q,t}$, and $SD_{QMJ,t}$ are value-weighted annualized three-month standard deviations of the quality stocks and the QMJ strategy respectively. All standard deviations are measured as decimals. REC_t is a recession dummy variable that is equal to one if any month in the quarter is a recession. We multiply all variables, except the returns and portfolio size, with the recession dummy to test the impact during recessions. The regression results are presented in Table 4.4. In column one, the results of regressing $\Delta QR_{n,t}$ on the market return variables is presented. Column two shows the impact of the recession dummy, before controlling for any of the variables. Columns three to six show the results of single-variable regressions and each respective variable multiplied by the recession dummy. The final column is the full regression as described in equation 4.1.

When controlling for all other variables, the results show that the recession dummy is statistically significant and has a positive effect on the change in the quality ratio. Considering that the change in quality ratio is mathematically restricted to being between -1 and 1, a magnitude of 0.289 indicates that there is a strong positive correlation between recessions and increases in quality ratio. In addition, the coefficient is twice the standard deviation of the delta quality ratio. Therefore, it can be inferred that the recession dummy has a strong impact on investors' preferences for quality. Based on the descriptive statistics shown above, we expect to see a positive correlation between recessions and the change in quality ratio. This result suggests that institutional investors

[12] All investor portfolios are ranked in ascending order and given a value between 0 (the smallest holdings) and 1 (the largest holdings) at time t

Table 4.4: Change in Quality Ratio Regression

	Dependent variable:						
	Delta Quality Ratio						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RET	0.025^{***}						0.088^{***}
	(0.003)						(0.004)
LAG RET	0.014^{***}						0.043^{***}
	(0.004)						(0.004)
PORT							-0.006^{***}
							(0.001)
REC		0.019^{***}	0.195^{***}	0.0003	-0.008^{***}	0.043^{***}	0.289^{***}
		(0.001)	(0.008)	(0.002)	(0.002)	(0.002)	(0.011)
MCAP Q			1.211^{***}				1.166^{***}
			(0.008)				(0.008)
REC * MCAP Q			-0.676^{***}				-0.929^{***}
			(0.028)				(0.041)
SD QMJ				0.155^{***}			0.322^{***}
				(0.006)			(0.008)
REC * SD QMJ				0.080^{***}			-0.210^{***}
				(0.012)			(0.015)
SD MARKET					-0.062^{***}		-0.383^{***}
					(0.005)		(0.011)
REC * SD MARKET					0.157^{***}		0.663^{***}
					(0.011)		(0.029)
SD Q						0.012^{**}	0.399^{***}
						(0.005)	(0.011)
REC * SD Q						-0.134^{***}	-0.709^{***}
						(0.012)	(0.026)
Constant	-0.004^{***}	-0.005^{***}	-0.343^{***}	-0.014^{***}	0.002^{***}	-0.006^{***}	-0.350^{***}
	(0.0003)	(0.0003)	(0.002)	(0.0005)	(0.001)	(0.001)	(0.002)
Observations	215,227	215,227	215,227	215,227	215,227	215,227	215,227
R^2	0.0003	0.002	0.105	0.007	0.003	0.003	0.118
Adjusted R^2	0.0003	0.002	0.105	0.007	0.003	0.003	0.118
Residual Std. Error	0.127 (df = 215224)	0.127 (df = 215225)	0.120 (df = 215223)	0.127 (df = 215223)	0.127 (df = 215223)	0.127 (df = 215223)	0.119 (df = 215214)
F Statistic	33.484^{***} (df = 2; 215224)	436.526^{***} (df = 1; 215225)	$8{,}382.487^{***}$ (df = 3; 215223)	505.795^{***} (df = 3; 215223)	238.284^{***} (df = 3; 215223)	187.789^{***} (df = 3; 215223)	$2{,}403.458^{***}$ (df = 12; 215214)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table shows results of quarterly time-series regressions of the change in quality ratio among institutional investors.
Columns 1 to 6 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAGRET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

move into quality stocks in recessions.

Looking into the interaction variables, one can further investigate the effect these have on the delta quality ratio, both during a recession and expansion. The coefficient of the volatility of the quality stocks is 0.399 during expansions and −0.709 during recessions. This suggests that the investors are more sensitive to volatility during recessions than expansions and move out of quality stocks if they become volatile in these periods. These results seem to be contradicting the fact that investors flee into quality during recessions, as the volatility of the stocks increases during recessions. The results indicate that investors do not mind volatility in quality stocks during expansions. On the contrary, the results suggest that institutional investors move out of quality stocks as their volatility decreases during expansions. This is expected as a flight to quality during recessions implies a divestment from quality during expansions. The coefficient of the market volatility shows a negative relationship to quality and QMJ. The coefficient is −0.383 during expansions and 0.663 during recessions. This can be explained by the fact that quality stocks are on average less volatile than the total market. However, the relationship suggests that the investors flee from volatile stocks during recessions in general. The fact that investors become more risk-averse during recessions is supported by the findings of Vayanos (2004). We can infer that this affects all stocks. The results suggest that as long as the market volatility increases more than the volatility of quality stocks, investors invest more in quality stocks. Investors might be chasing risky returns during expansions.

The relationship between the institutional investor's portfolio size and the quality ratio of that investor is −0.006, slightly negative. Although the magnitude is low, the negative sign suggests that larger investors go less into quality stocks. This is natural as larger investors diversify more and the mean quality ratio is larger than the market cap of quality stocks would suggest. The market share of the quality stocks has a coefficient of 1.166 during expansions, suggesting that when the quality stocks become larger relative to other stocks, investors deliberately go into quality stocks. A coefficient above 1 suggests that the increase is not only mechanical, as the market share of quality stocks increases. The coefficient is −0.929 during recessions, suggesting counter-intuitively that the mechanical change impacts the quality ratio in a negative manner. As both the quality ratio and relative market share of quality stocks increase during recessions, the positive trend in quality ratio could be captured by the recession dummy.

4.3.2 Junk Ratio

In the second regression, we look at the junk stocks and use the change in junk ratio as dependent variable. The structure of the regression is similar to equation 4.1, with the difference that the quality stocks are replaced with junk stocks. The purpose of this regression is to test whether investors flee from, stay in, or flee to junk stocks during recessions:

$$\Delta JR_{n,t} = \alpha + \beta_1 Ret_t + \beta_2 Ret_{t-1} + \beta_3 Port_{n,t} + \beta_4 MC_{J,t} + \beta_5 SD_{J,t} + \beta_6 SD_{M,t} + \beta_7 SD_{QMJ,t}$$
$$+ \beta_8 REC_t + \beta_9 REC_t * SD_{QMJ,t} + \beta_{10} REC_t * MC_{J,t} + \beta_{11} REC_t * SD_{J,t} + \beta_{12} REC_t * SD_{M,t} + \epsilon_t \tag{4.2}$$

Where the $\Delta JR_{n,t}$ is the change in junk ratio for the institutional investor n at time t. $MC_{J,t}$ is the market share of all junk stocks relative to the total stock market at time t. $SD_{J,t}$ is the value-weighted annualized three-month standard deviations of the junk stocks at time t. All other variables are equal to that described in section 4.3.1. Similar to the first regression, we multiply all variables, except the returns and portfolio size, with the recession dummy to test the impact during recessions.

The coefficient of the recession dummy is -0.015 when controlling only for the market value of junk stocks and 0.009 when only controlling for the volatility of junk stocks. In all other regressions, the recession dummy is not statistically significant, implying that a change in junk ratio is not explained by recessions. This suggests that although institutional investors move towards quality stocks during a recession, they do not necessarily move out of the junk stocks. Although junk stocks are presumed to perform poorly during recessions, this is in line with the observations in the descriptive statistics in 4.3.

Looking at the coefficients of the volatility of the market, 0.034 during expansions suggests that it has almost no impact on investors' junk ratios. A coefficient of 0.524 during recessions suggests that investors move into junk stocks as the volatility of the market goes up. Although this can be counter-intuitive, the coefficient of the volatility of junk stocks during recessions is -0.392, mitigating the impact of the market volatility. This can be

Table 4.5: Delta Junk Ratio Regression

	Dependent variable: Delta Junk Ratio						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RET	−0.020***						−0.016***
	(0.003)						(0.003)
LAG RET	0.047***						0.052***
	(0.003)						(0.003)
PORT							−0.003***
							(0.001)
REC		−0.0004	−0.015***	−0.001	0.001	0.009***	−0.009
		(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.006)
MCAP J			0.393***				0.387***
			(0.006)				(0.007)
REC * MCAP J			0.139***				0.060
			(0.023)				(0.045)
SD QMJ				0.043***			0.085***
				(0.005)			(0.007)
REC * SD QMJ				−0.018*			0.077***
				(0.009)			(0.029)
SD MARKET					−0.020***		0.034***
					(0.003)		(0.008)
REC * SD MARKET					0.005		0.524***
					(0.008)		(0.047)
SD J						0.005*	−0.066***
						(0.003)	(0.008)
REC * SD J						−0.035***	−0.392***
						(0.006)	(0.048)
Constant	−0.001***	−0.001***	−0.044***	−0.003***	0.001***	−0.001***	−0.044***
	(0.0002)	(0.0002)	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.001)
Observations	213,252	213,252	213,252	213,252	213,252	213,252	213,252
R^2	0.002	0.00000	0.021	0.0004	0.0002	0.0002	0.024
Adjusted R^2	0.002	-0.00000	0.021	0.0004	0.0002	0.0002	0.024
Residual Std. Error	0.095 (df = 213249)	0.095 (df = 213250)	0.094 (df = 213248)	0.095 (df = 213248)	0.095 (df = 213248)	0.095 (df = 213248)	0.094 (df = 213239)
F Statistic	182.415*** (df = 2; 213249)	0.370 (df = 1; 213250)	1,502.877*** (df = 3; 213248)	29.775*** (df = 3; 213248)	12.783*** (df = 3; 213248)	11.801*** (df = 3; 213248)	436.407*** (df = 12; 213239)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in junk ratio among institutional investors.
Columns 1 to 6 show the results of single-variable regressions with the change in junk ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAGRET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPJ is the market share of junk stocks at time t. SDQMJ and SDJ are the value-weighted annualized three-month standard deviations of the QMJ strategy and junk stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPJ and the volatility measures to measure the difference during expansions and recessions.

due to stocks mechanically being downgraded to junk during high volatility, leading to involuntary bets on junk. However, it can be inferred that institutional investors leave junk stocks as they become more volatile, as long as the market is not more volatile. In other words, institutional investors become more sensitive to volatility during recessions.

The results suggest that institutional investors invest similar portions of their holdings in junk stocks, regardless of size. The market share of the junk stocks has a coefficient of 0.387 during expansions, which could be mechanical due to junk stocks increasing in size. However, it is relatively low compared to the coefficient of the quality market share. It can be inferred that institutional investors favor quality stocks that perform well over junk stocks that perform poorly. On the other hand, the coefficient is not statistically significant during recessions, suggesting that the change in junk ratio is explained by other independent variables.

4.3.3 QMJ Ratio

The third regression in this section looks at the change in the QMJ ratio as the dependent variable. The delta QMJ ratio is the change in quality ratio minus junk ratio of each institutional investor over time. It measures whether the spread between the ratios increases during expansions and recessions. This is to check that the results observed in the two earlier regressions are consistent. If the institutional investors herd to quality stocks during recessions, similar results to the quality ratio regression are expected. The regression can also help explain whether investors favor quality over junk. The structure of the regression is similar to equation 4.1, except that the dependent variable is the change in quality ratio minus junk ratio:

$$\Delta QMJ_{n,t} = \alpha + \beta_1 Ret_t + \beta_2 Ret_{t-1} + \beta_3 Port_{n,t} + \beta_4 MC_{Q,t} + \beta_5 SD_{Q,t} + \beta_6 SD_{M,t} + \beta_7 SD_{QMJ,t}$$
$$+ \beta_8 REC_t + \beta_9 REC_t * SD_{QMJ,t} + \beta_{10} REC_t * MC_{Q,t} + \beta_{11} REC_t * SD_{Q,t} + \beta_{12} REC_t * SD_{M,t} + \epsilon_t \quad (4.3)$$

Where the $\Delta QMJ_{n,t}$ is the change in quality ratio minus junk ratio for the institutional investor n at time t. All other variables are the same as described in section 4.3.1. Similar to the first regression, we multiply all variables, except the returns and portfolio size, with the recession dummy to test the impact during recessions.

Table 4.6: Delta QMJ Ratio Regression

	Dependent variable: Delta QMJ Ratio						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RET	0.048***						0.120***
	(0.004)						(0.005)
LAG RET	−0.029***						0.008*
	(0.004)						(0.005)
PORT							−0.004***
							(0.001)
REC		0.019***	0.147***	0.001	−0.007***	0.025***	0.191***
		(0.001)	(0.010)	(0.002)	(0.003)	(0.003)	(0.013)
MCAP Q			0.926***				0.905***
			(0.009)				(0.009)
REC * MCAP Q			−0.490***				−0.641***
			(0.033)				(0.047)
SD QMJ				0.106***			0.215***
				(0.007)			(0.009)
REC * SD QMJ				0.105***			−0.048***
				(0.014)			(0.018)
SD MARKET					−0.038***		−0.200***
					(0.005)		(0.013)
REC * SD MARKET					0.143***		0.196***
					(0.012)		(0.034)
SD Q						−0.005	0.227***
						(0.006)	(0.012)
REC * SD Q						−0.028**	−0.180***
						(0.014)	(0.031)
Constant	−0.002***	−0.004***	−0.262***	−0.011***	0.0001	−0.003***	−0.273***
	(0.0003)	(0.0003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	204,275	204,275	204,275	204,275	204,275	204,275	204,275
R^2	0.001	0.002	0.050	0.004	0.002	0.002	0.056
Adjusted R^2	0.001	0.002	0.050	0.004	0.002	0.002	0.056
Residual Std. Error	0.141 (df = 204272)	0.141 (df = 204273)	0.138 (df = 204271)	0.141 (df = 204271)	0.141 (df = 204271)	0.141 (df = 204271)	0.137 (df = 204262)
F Statistic	99.294*** (df = 2; 204272)	364.475*** (df = 1; 204273)	3,620.038*** (df = 3; 204271)	292.652*** (df = 3; 204271)	169.748*** (df = 3; 204271)	124.092*** (df = 3; 204271)	1,015.355*** (df = 12; 204262)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio minus junk ratio among institutional investors.
Columns 1 to 6 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAGRET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

The coefficient of the recession dummy is 0.191, suggesting that the spread between quality ratio and junk ratio increases during recessions. However, the coefficient is lower than the recession dummy coefficient for the quality ratio alone. This implies that while institutional investors move into quality stocks during recessions, they may not necessarily leave junk stocks.

The change in quality ratio minus junk ratio is not highly affected by the volatility measures. As in previous regressions, the results suggest that investors become more risk-averse during recessions. An interesting aspect is the impact of quality stocks' volatility during recessions, with a coefficient of -0.180. This suggests that the spread between quality ratio and junk ratio decreases as quality stocks become more volatile. This implies that, as the volatility of quality stocks goes up, investors either invest more in junk stocks than quality stocks or sell more quality stocks than junk stocks during recessions. The effect is mitigated by the volatility of the market during recessions.

The market share of quality stocks has a coefficient of -0.641 during recessions, suggesting that as quality stocks become a larger share of the market, investors move out from quality or into junk. This is counter-intuitive because quality stocks gain a larger share of the market during recessions and we observe an overall positive trend into quality stocks. One possible explanation to this is that the change in market share of quality during the recession in 2001 is negative. Another possible explanation is that the recession dummy captures much of the change. The portfolio size has a slightly negative coefficient, suggesting that larger investors diversify more.

Overall, the results obtained from the regression on the delta QMJ ratio are in line with the earlier regressions. It is possible to infer that institutional investors favor quality stocks during recessions, but it is not clear that they move out from junk stocks. The junk ratio is close to the market share of junk stocks, suggesting that this can be driven by diversification strategies rather than active bets.

4.3.4 Adjusted Quality Ratio

The plots in section 4.2 suggest that the change in quality ratio may be due to mechanical adjustments in the market share of quality stocks. The previous regression results show evidence that supports a *flight to quality*. The results are not coherent and slightly contradicting. To test whether the change in quality ratio is mechanical, we first compute the change in adjusted quality ratio:

$$\Delta ADJQR_{n,q,t} = (QR_{n,q,t} - MCap_{q,t}) - (QR_{n,q,t-1} - MCap_{q,t-1}) \tag{4.4}$$

Where $QR_{n,q,t}$ is the quality ratio of investor n at time t and $MCap_{q,t}$ is the market share of quality stocks. We then do a regression on the change in adjusted quality ratio. In other words, the dependent variable is the change in institutional investors' active bet on quality stocks:

$$\begin{aligned}\Delta ADJQR_{n,t} = \alpha + \beta_1 Ret_t + \beta_2 Ret_{t-1} + \beta_3 Port_{n,t} + \beta_4 SD_{Q,t} + \beta_5 SD_{M,t} + \beta_6 SD_{QMJ,t} \\ + \beta_7 REC_t + \beta_8 REC_t * SD_{QMJ,t} + \beta_9 REC_t * SD_{Q,t} + \beta_{10} REC_t * SD_{M,t} + \epsilon_t\end{aligned} \tag{4.5}$$

The regression is similar to equation 4.1, except that the market share of quality stocks is excluded because it is incorporated in the dependent variable. The regression results are shown in table 4.7. Even after adjusting for the market share of quality stocks, the recession dummy is statistically significant and has a coefficient of 0.030. The magnitude is lower than before adjusting the quality ratio, in nominal terms. However, the impact is still noteworthy considering this is measuring the change in active quality bets and the average adjusted quality ratio is around 0.04. The results presented in table 4.7 show evidence that there is a flight to quality during recessions, even after adjusting for the market share of quality stocks.

We find evidence that the QMJ strategy has low volatility and performs well during recessions. The returns come from shorting the seemingly riskier junk stocks. Despite this, our findings suggest that the bet on junk has an upward trend among institutional investors and that they remain invested in junk stocks throughout the recessions. Although the increase in quality ratio among institutional investors can partly be attributed to the increase in market share of quality stocks, the investors bet disproportionately larger amounts in quality stocks during recessions. Even when only analyzing the active bets in quality made by the investors, the evidence suggests investors flee to quality stocks within

Table 4.7: Delta Adjusted Quality Ratio Regression

	Dependent variable:					
	Adjusted Delta QR Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
RET	0.042***					0.051***
	(0.003)					(0.004)
LAG RET	0.021***					0.061***
	(0.003)					(0.004)
PORT						−0.007***
						(0.001)
REC		0.007***	−0.023***	0.007***	0.059***	0.030***
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
SD QMJ			0.003			0.098***
			(0.006)			(0.007)
REC * SD QMJ			0.250***			0.052***
			(0.011)			(0.014)
SD MARKET				0.014***		−0.206***
				(0.004)		(0.010)
REC * SD MARKET				−0.007		0.588***
				(0.010)		(0.022)
SD Q					0.064***	0.262***
					(0.004)	(0.010)
REC * SD Q					−0.306***	−0.795***
					(0.011)	(0.022)
Constant	−0.004***	−0.003***	−0.003***	−0.004***	−0.009***	−0.013***
	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.001)
Observations	215,227	215,227	215,227	215,227	215,227	215,227
R^2	0.001	0.0004	0.004	0.0004	0.004	0.015
Adjusted R^2	0.001	0.0004	0.004	0.0004	0.004	0.015
Residual Std. Error	0.113 (df = 215224)	0.114 (df = 215225)	0.113 (df = 215223)	0.114 (df = 215223)	0.113 (df = 215223)	0.113 (df = 215216)
F Statistic	118.714*** (df = 2; 215224)	84.454*** (df = 1; 215225)	265.328*** (df = 3; 215223)	32.141*** (df = 3; 215223)	301.241*** (df = 3; 215223)	320.146*** (df = 10; 215216)
Note:						*p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio minus the market share of the quality stocks among institutional investors. Columns 1 to 5 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAGRET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with the volatility measures to measure the difference during expansions and recessions.

the US equity market during recessions. We can infer that institutional investors herd to quality stocks but do not leave junk stocks during recessions. It is not clear which stocks the investors move out from or why they remain invested in junk stocks during recessions. This leaves room for future research. However, our findings support the notion of *flight to quality* within the US equity market during recessions.

5 Robustness

In this chapter, we present robustness tests for the results obtained in the empirical analysis. First, we analyze the change in quality ratio among investors who do not bet more than 30% in any individual stock and have a quality ratio in the bottom 80%. This is to test whether the results can be attributed to investors who typically bet heavily on quality or individual stocks. Second, we replace the recession dummy with a dummy equal to one when the previous quarterly return is strictly negative. The purpose is to examine if shorter-term market downturns lead to a flight to quality within the US equity market. In addition, this tests whether our results are driven by recessions and not by a variation in the definition of a market downturn. Lastly, we compare the quality components individually to test whether institutional investors favor a particular component during recessions or if they need to be combined.

5.1 Pruned Quality Ratio

The pruned quality measure excludes institutional investors with the top 20% quality ratios at every quarter and those that have more than 30% in any individual stock. The argument for this robustness test is to check whether quality investors drive the positive coefficient found for the recession dummy. Quality investors would be investors specifically investing in quality stocks and hence do not move into quality explicitly in recessions, but instead are heavily invested in the strategy in all periods. The pruned quality ratio removes institutional investors, which hold a position of one quality stock over 30%, indicating that one quality stock drives a significant part of their quality ratio. In addition, removing the investors with large positions reduces the chance of the change in quality ratio being driven by stocks changing quality groups. If a stock the investor is heavily invested in moves from the junk portfolio to the quality, the investor would not purposefully bet on quality. Therefore, if the previously presented results are robust and not driven by large quality investors or large positions moving across portfolios, one would see similar results.

The pruned quality ratio gives comparable results to what is given by the quality ratio. The recession dummy gives still a positive coefficient, with just a minor decrease in magnitude. This is expected due to investors with the highest quality ratio being removed

Table 5.1: Pruned Delta Quality Ratio

	Dependent variable:						
	Delta Quality Ratio Pruned						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RET	0.051***						0.134***
	(0.004)						(0.005)
LAG RET	0.006						0.035***
	(0.004)						(0.005)
PORT							0.013***
							(0.001)
REC		0.011***	0.154***	−0.004**	−0.001	0.045***	0.229***
		(0.001)	(0.011)	(0.002)	(0.003)	(0.003)	(0.013)
MCAP Q			0.895***				0.851***
			(0.009)				(0.009)
REC * MCAP Q			−0.549***				−0.730***
			(0.035)				(0.049)
SD QMJ				0.138***			0.339***
				(0.007)			(0.009)
REC * SD QMJ				0.060***			−0.205***
				(0.015)			(0.019)
SD MARKET					0.007		−0.458***
					(0.005)		(0.013)
REC * SD MARKET					0.050***		0.611***
					(0.013)		(0.037)
SD Q						0.092***	0.527***
						(0.006)	(0.013)
REC * SD Q						−0.228***	−0.679***
						(0.015)	(0.033)
Constant	−0.028***	−0.028***	−0.274***	−0.036***	−0.028***	−0.037***	−0.299***
	(0.0003)	(0.0003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	126,955	126,955	126,955	126,955	126,955	126,955	126,955
R^2	0.001	0.001	0.068	0.005	0.001	0.004	0.089
Adjusted R^2	0.001	0.001	0.068	0.005	0.001	0.004	0.089
Residual Std. Error	0.116 (df = 126952)	0.116 (df = 126953)	0.112 (df = 126951)	0.116 (df = 126951)	0.116 (df = 126951)	0.116 (df = 126951)	0.111 (df = 126942)
F Statistic	77.042*** (df = 2; 126952)	91.133*** (df = 1; 126953)	3,070.768*** (df = 3; 126951)	221.027*** (df = 3; 126951)	37.999*** (df = 3; 126951)	151.598*** (df = 3; 126951)	1,038.804*** (df = 12; 126942)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio among institutional investors that do not bet more than 30% in any individual stock and have a quality ratio in the bottom 80%.

Columns 1 to 6 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAG RET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

and the overall quality ratio with the pruned one is lower. In addition, the other variables have the same direction and only have slightly lower coefficients. The exception from this is the investor's portfolio value, which previously has a negative correlation with the change in quality ratio. Now the correlation is positive, meaning that the larger investors go more into quality stocks. What leads to this change might be that the normal quality ratio contains small investors with large-quality positions, that when removed, changes the coefficient.

As mentioned, removing the investors holding more than 30% position in one quality stocks reduces the chance of unintentional bets on quality when the stocks change groups. We investigate this further to see whether the change in quality (or junk) ratio done by institutional investors is done intentionally, or because the stocks simply change between the different groups. In order to do so, we look at the change in value scaled to total market value, that the institutional investors in total hold in stocks changing from junk to quality or quality to junk. On average during an expansion, the delta value to total market value increases 23% when the stock changes from junk to quality, and reduces 14% when the stock goes from quality to junk. During a recession, the stocks going from junk to quality increases 85%, while the stock going from quality to junk decreases 88%. This further supports the notion that the institutional investors herd on quality stocks during recessions, and this intentionally.

5.2 Negative Return Periods

The data set used for the institutional investor holdings contains ten quarters of recessions. At the very beginning, the investor will not know whether the period of negative returns is a short-term market correction or a recession. To investigate the *flight to quality* further, we regress the delta quality ratio with a variation of a market downturn. We replace the recession dummy with a new dummy variable equal to one when the past quarterly return is negative. If the previously presented results are robust, one could expect similar results obtained with the recession dummy. If the quality herding exists, one would expect the herding to happen already when the market shows signs of a downturn, even if it ends up not being a long-term one. The investors are then assumed to already at this time move towards quality stocks.

The coefficients of the independent variables show the same direction of influence on the change in quality ratio, as one achieved using the recession dummy. The increased volatility of the quality stocks and the QMJ factor decreases the quality ratio, while the market volatility increases the ratio when there is a negative return on the market. The dummy for previous negative quarterly returns is positive, indicating that the investors move towards quality stocks when the market has a downturn. However, the coefficient is lower than what is seen with the recession dummy. The lower coefficient suggests that the investors increase their quality ratio when the market returns are negative over the longer term.

5.3 Flight to Profit, Growth or Safety?

In earlier studies, general *flight to quality* describes investor flight to safer assets, usually bonds. Investors are generally more risk-averse during market downturns (Vayanos, 2004) and might flee to quality due to the safety factor, and not the quality in itself. In this section, the quality measures are separated, and the portfolio creation is based on a Z-score calculated on the specific measurements alone. The motivation behind this is to be able to pinpoint the specific attribute the investors move towards during recessions. If the investors flee to quality because of the safety factor, one could expect to see a positive and comparable coefficient for the recession dummy as seen in table 4.4 when the quality consists only of safety. The three different quality measures are calculated as follows:

$$Quality_G = z(Growth) \tag{5.1}$$

$$Quality_P = z(Profitability) \tag{5.2}$$

$$Quality_S = z(Safety) \tag{5.3}$$

Tables 5.3, 5.4, and 5.5 show the regression of the change in quality ratios among institutional investors, using the growth, profitability, and safety as individual quality measures. In other words, the stocks are given a quality scores as described in equations 5.1, 5.2, and 5.3. The recession coefficient is positive and significant when ranking the stocks on either profitability or growth. Although the magnitude is lower, this is in line with the findings in chapter 4 and support the notion *flight to quality*. However, the

Table 5.2: Change in Quality Ratio Regression with Negative Return Dummy

	Dependent variable:					
	Delta Quality Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
PORT						-0.006^{***}
						(0.001)
RECNEG	0.008^{***}	0.055^{***}	0.026^{***}	-0.014^{***}	0.0001	0.050^{***}
	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)	(0.005)
MCAP Q		1.190^{***}				1.104^{***}
		(0.008)				(0.009)
RECNEG * MCAP Q		-0.183^{***}				-0.052^{***}
		(0.017)				(0.019)
SD QMJ			0.317^{***}			0.429^{***}
			(0.007)			(0.008)
RECNEG * SD QMJ			-0.304^{***}			-0.476^{***}
			(0.011)			(0.014)
SD MARKET				-0.075^{***}		-0.457^{***}
				(0.005)		(0.012)
RECNEG * SD MARKET				0.170^{***}		0.467^{***}
				(0.008)		(0.021)
SD Q					-0.014^{**}	0.420^{***}
					(0.006)	(0.012)
RECNEG * SD Q					0.058^{***}	-0.496^{***}
					(0.009)	(0.020)
Constant	-0.005^{***}	-0.339^{***}	-0.024^{***}	0.002^{***}	-0.004^{***}	-0.329^{***}
	(0.0003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	215,227	215,227	215,227	215,227	215,227	215,227
R^2	0.001	0.103	0.010	0.003	0.001	0.115
Adjusted R^2	0.001	0.103	0.010	0.003	0.001	0.115
Residual Std. Error	0.127 (df = 215225)	0.121 (df = 215223)	0.127 (df = 215223)	0.127 (df = 215223)	0.127 (df = 215223)	0.120 (df = 215216)
F Statistic	174.614^{***} (df = 1; 215225)	$8{,}198.487^{***}$ (df = 3; 215223)	733.048^{***} (df = 3; 215223)	205.494^{***} (df = 3; 215223)	72.281^{***} (df = 3; 215223)	$2{,}805.939^{***}$ (df = 10; 215216)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio among institutional investors.
Columns 1 to 5 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 6 shows the result of the multiple regression containing all row variables. Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. RECNEG is a recession dummy that is equal to one if the quarterly returns from quarter t-1 to t are negative. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

recession coefficient is -0.082 when ranking stocks using only the safety component. This does not reject the idea that investors flee to safety, as stocks that rank high on the combined quality measure can be even safer. However, this suggests that investors may prioritize other stock characteristics over safety.

The high and positive coefficient found for the recession dummy in table 4.4, but not in table 5.3, table 5.4 or table 5.5, implies that the highly significant results in table 4.4 shows an investor herding towards quality stocks. The significant results do not stem from investors that move towards stocks that score high profitability, growth, or safety, which are attractive attributes when there is a market downturn. These results are a strong indicator that the results found in this thesis show investors *flight to quality* within the US equity market.

Table 5.3: Delta Growth Ratio

	Dependent variable:					
	Delta Quality Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
RET	−0.005					−0.041***
	(0.003)					(0.003)
LAG RET	0.015***					0.013***
	(0.003)					(0.004)
PORT						−0.004***
						(0.001)
REC		0.012***	−0.005*	0.064***	0.006***	0.089***
		(0.001)	(0.003)	(0.002)	(0.002)	(0.003)
MCAP Q			0.255***			0.262***
			(0.005)			(0.005)
REC * MCAP Q			0.056***			−0.080***
			(0.012)			(0.013)
SD Q				0.036***		0.122***
				(0.004)		(0.008)
REC * SD Q				−0.287***		−1.100***
				(0.012)		(0.024)
SD MARKET					0.019***	−0.091***
					(0.004)	(0.008)
REC * SD MARKET					0.019**	0.667***
					(0.009)	(0.019)
Constant	−0.001***	−0.002***	−0.051***	−0.006***	−0.004***	−0.053***
	(0.0002)	(0.0002)	(0.001)	(0.0005)	(0.0005)	(0.001)
Observations	216,499	216,499	216,499	216,499	216,499	216,499
R^2	0.0001	0.001	0.017	0.004	0.001	0.027
Adjusted R^2	0.0001	0.001	0.017	0.004	0.001	0.027
Residual Std. Error	0.107 (df = 216496)	0.107 (df = 216497)	0.106 (df = 216495)	0.107 (df = 216495)	0.107 (df = 216495)	0.105 (df = 216488)
F Statistic	13.585*** (df = 2; 216496)	268.602*** (df = 1; 216497)	1,257.799*** (df = 3; 216495)	287.896*** (df = 3; 216495)	105.197*** (df = 3; 216495)	612.164*** (df = 10; 216488)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio among institutional investors, using only the growth component of quality.
Columns 1 to 6 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAG RET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

Table 5.4: Delta Profitability Ratio

	Dependent variable: Delta Quality Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
RET	−0.003					0.011***
	(0.003)					(0.004)
LAG RET	0.008**					0.055***
	(0.003)					(0.004)
PORT						−0.008***
						(0.001)
REC		0.015***	0.118***	0.021***	−0.017***	0.050***
		(0.001)	(0.009)	(0.002)	(0.002)	(0.011)
MCAP Q			1.268***			1.206***
			(0.010)			(0.010)
REC * MCAP Q			−0.406***			−0.059
			(0.032)			(0.045)
SD Q				0.103***		0.462***
				(0.005)		(0.010)
REC * SD Q				−0.081***		−0.755***
				(0.011)		(0.020)
SD MARKET					−0.037***	−0.413***
					(0.004)	(0.009)
REC * SD MARKET					0.169***	0.574***
					(0.010)	(0.019)
Constant	−0.002***	−0.004***	−0.353***	−0.014***	0.0001	−0.338***
	(0.0003)	(0.0003)	(0.003)	(0.001)	(0.001)	(0.003)
Observations	215,197	215,197	215,197	215,197	215,197	215,197
R^2	0.00003	0.001	0.074	0.004	0.003	0.087
Adjusted R^2	0.00002	0.001	0.074	0.004	0.003	0.087
Residual Std. Error	0.121 (df = 215194)	0.121 (df = 215195)	0.116 (df = 215193)	0.121 (df = 215193)	0.121 (df = 215193)	0.116 (df = 215186)
F Statistic	3.074** (df = 2; 215194)	314.773*** (df = 1; 215195)	5,743.040*** (df = 3; 215193)	264.250*** (df = 3; 215193)	197.960*** (df = 3; 215193)	2,061.050*** (df = 10; 215186)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio among institutional investors, using only the profitability component of quality.
Columns 1 to 6 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAG RET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a recession dummy that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

Table 5.5: Delta Safety Ratio

	Dependent variable:					
	Delta Quality Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
RET	−0.068***					0.010**
	(0.003)					(0.004)
LAG RET	0.080***					0.160***
	(0.004)					(0.004)
PORT						−0.009***
						(0.001)
REC		0.013***	−0.015	0.031***	0.001	−0.082***
		(0.001)	(0.011)	(0.002)	(0.002)	(0.015)
MCAP Q			0.900***			0.901***
			(0.007)			(0.008)
REC * MCAP Q			0.027			0.311***
			(0.031)			(0.044)
SD Q				0.053***		0.175***
				(0.005)		(0.011)
REC * SD Q				−0.129***		−0.217***
				(0.014)		(0.033)
SD MARKET					−0.030***	−0.071***
					(0.005)	(0.010)
REC * SD MARKET					0.073***	0.082***
					(0.011)	(0.027)
Constant	−0.002***	−0.003***	−0.296***	−0.008***	−0.0002	−0.307***
	(0.0003)	(0.0003)	(0.002)	(0.001)	(0.001)	(0.003)
Observations	215,196	215,196	215,196	215,196	215,196	215,196
R^2	0.004	0.001	0.072	0.002	0.001	0.081
Adjusted R^2	0.004	0.001	0.072	0.002	0.001	0.081
Residual Std. Error	0.129 (df = 215193)	0.129 (df = 215194)	0.124 (df = 215192)	0.129 (df = 215192)	0.129 (df = 215192)	0.124 (df = 215185)
F Statistic	435.153*** (df = 2; 215193)	213.964*** (df = 1; 215194)	5,555.437*** (df = 3; 215192)	117.093*** (df = 3; 215192)	91.749*** (df = 3; 215192)	1,907.283*** (df = 10; 215185)

Note: *p<0.1; **p<0.05; ***p<0.01

This table shows results of quarterly time-series regressions of the change in quality ratio among institutional investors, using only the safety component of quality.
Columns 1 to 6 show the results of single-variable regressions with the change in quality ratio as the dependent variable and the row variable as the independent variable. Column 7 shows the result of the multiple regression containing all row variables. RET is the quarterly return at time t and LAG RET is the previous quarterly returns (quarterly returns at time t-1). Port is the portfolio size of the investors and is measured on a ranked basis where the smallest investor has a value of zero and the largest investor has a value of one, at quarter t. MCAPQ is the market share of quality stocks at time t. SDQMJ and SDQ are the value-weighted annualized three-month standard deviations of the QMJ strategy's and quality stocks' returns, respectively, at time t. SDMARKET is the annualized three-month standard deviation of the market returns. REC is a dummy variable that is equal to one if any of the months within a quarter t is defined as a recession month according to the NBER definition. The recession dummy is multiplied with MCAPQ and the volatility measures to measure the difference during expansions and recessions.

6 QMJ and Momentum

Chapter 4 finds evidence that the QMJ strategy performs well and sustains relatively low volatility during recessions. The high returns are documented by Asness et al. (2019) and persist regardless of whether there is a *flight to quality* or not. In this chapter, we test whether combining the QMJ strategy with the winners-minus-losers (WML) momentum strategy helps avoid momentum crashes. As an additional contribution, the sole purpose of this chapter is to test the viability of using the QMJ as a hedge toward recessions. The motivation behind this chapter is that momentum strategies are prone to crash during market distress (Daniel and Moskowitz, 2016), which usually occurs during market downturns. To test whether the QMJ strategy can be used as a hedge, we first create an arbitrary 50/50 QMJ-WML joint-strategy portfolio. The joint-strategy portfolio is inspired by the joint-strategy portfolio constructed by Asness et al. (2013). We then create a joint strategy portfolio with a dynamic weighting scheme. We use the scalar construct by Barroso and Santa-Clara (2015) as a "crash predictor", betting more heavily in QMJ when the volatility of WML goes up and more into WML when the volatility is low. The purpose is not to find the best way to use QMJ as a hedge but rather to test whether it is possible to exploit its abnormal returns by simple measures.

6.1 QMJ as Risk Mitigation for WML

Because QMJ performs the best during recessions, it could be used as a hedging strategy for strategies that suffer from them. Daniel and Moskowitz (2016) find evidence that despite a strong overall performance, the WML momentum strategy cannot sustain its abnormal profits in the long term due to a few major losses. The largest losses occur during market distress and following financial crises. One of the worst-performing periods for WML is after the 2007-2009 financial crisis (Daniel and Moskowitz, 2016). During the same period, QMJ outperformed the market. If WML suffers at times when QMJ gain, the two strategies could be combined to exploit both low- and high-volatile markets.

Research shows that the risks of momentum crashes can be mitigated by forecasting the volatility. Barroso and Santa-Clara (2015) show that by creating a dynamic scalar using simple backwards-looking volatility measures, the Sharpe ratio increases sharply, and the risk for crashes dramatically lower. The intuition behind the scalar is that during low-volatility markets, the investor should invest more in WML (sometimes above 100%), and during market distress, the investor should scale down the WML bet. Another way of interpreting the scalar is that high volatility is an indicator of a market downturn. Therefore, we want to create an investment strategy that invests heavily in QMJ during high volatility and WML during low volatility.

To use QMJ as a hedge for WML, we want to create a joint strategy portfolio. We form QMJ portfolios and go long the top 30% and short the bottom 30%, as described in chapter 3.4. For WML, we download the decile-sorted momentum portfolios from Fama and French's website and go long the top 10% winners and short the bottom 10% [13]. We begin with an arbitrary 50/50 weight scheme where we invest equally in the two portfolios:

$$0.5QMJ + 0.5WML \tag{6.1}$$

We follow the methodology presented in Barroso and Santa-Clara (2015) and forecast the momentum risk by computing a variance forecast $\hat{\sigma}_t^2$ from previous daily WML returns[14]. In their paper, the authors use the six previous months. However, they also document that using return data in the previous one and three months gives similar results (Barroso and Santa-Clara, 2015). We choose to use the previous three months' data[15] to spot market downturns earlier:

$$\hat{\sigma}^2_{WML_t} = 21 \sum_{j=0}^{62} r^2_{WML,d_{t-1}-j}/63 \tag{6.2}$$

We then calculate the scalar for each month:

$$Scalar = \frac{\sigma_{target}}{\hat{\sigma}_t^2} \tag{6.3}$$

As in the original paper, we choose target volatility of 12%. The scalar is then incorporated

[13] Following the methodology of Barroso and Santa-Clara (2015)

[14] See C for replication results

[15] We use the ten portfolio monthly momentum data found on Fama and French's website from January 1927 to December 2020. The daily momentum data from 1927 to June 1963 is downloaded from Kent Daniel's website. The daily data from July 1963 to December 2020 is downloaded from Fama and French's website.

into a dynamic weight scheme:

$$Portfolio = 0.5(QMJ * (2 - Scalar) + WML * Scalar) \tag{6.4}$$

The intuition behind the weighting scheme is that the investor can scale up QMJ when WML is risky and scale up WML when it is less risky. The monthly portfolio returns are:

$$r_{Port} = 0.5 * (r_{QMJ,t}(2 - Scalar) + r_{WML,t} * Scalar) \tag{6.5}$$

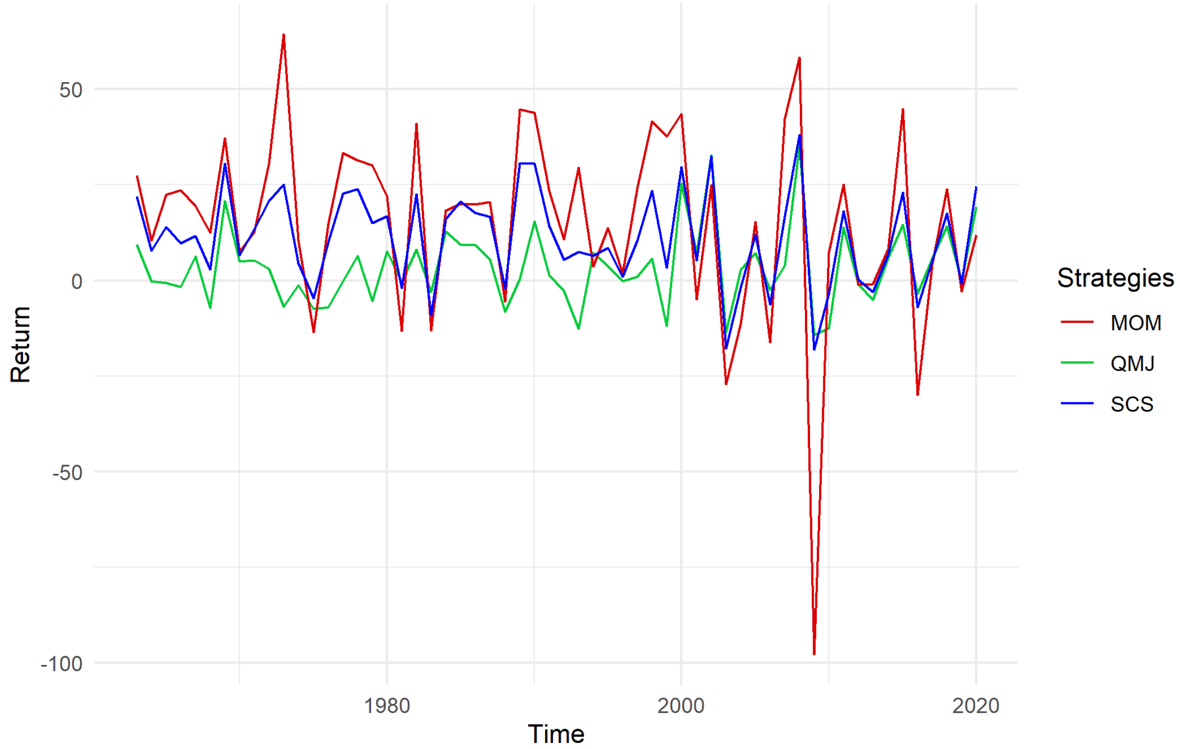
where $r_{QMJ,t}$ and $r_{WML,t}$ are the monthly QMJ and WML returns at time t.

6.2 Results and Implications

The monthly return from July 1957 to June 2020 of the momentum, quality, and the scaled strategy is shown in figure 6.1. The momentum strategy generates high returns, and QMJ contributes to lowering the overall volatility of the portfolio. The momentum crash in 2009 shows that QMJ can be used jointly with momentum strategies to hedge against market crashes. Although the results are negative for all portfolios, the momentum returns almost eradicate the portfolio gains, which is what Daniel and Moskowitz (2016) warn about.

The median and mean scalar are 0.87 and 0.94, respectively, meaning that our strategy mostly puts higher weight on the QMJ than the WML strategy. The excess return and the factor loadings of the strategies are presented in table 6.1. The arbitrary 50/50 portfolio gives a higher Sharpe ratio than both the QMJ and the WML strategy alone. Asness et al. (2013) combine momentum with a value strategy in the same manner, giving better results than momentum and QMJ, with 0.86 in Sharpe ratio; this is likely because the correlation between value and momentum Asness et al. (2013) finds is -0.65, while for momentum and our QMJ factor it is 0.37. Although value may perform better than QMJ with momentum, we prove that the QMJ strategy can enhance momentum strategies and mitigate momentum crashes.

Figure 6.1: Annualized Mean Return of Strategies



The plot shows the annualized monthly average return of the WML factor, the QMJ factor, and a combination of the factors using a dynamic scalar. The sample period runs from July 1957 until June 2020. The WML factor is downloaded through Kenneth French's data libraryFrench, K. (2021). The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality, refreshed and re-balanced monthly to sustain the value weights. The size breakpoints are constructed using the median NYSE market equity. After sorting on size, the portfolios are sorted on quality. The QMJ factor is the average return on the two high-quality portfolios minus the average return on the low-quality portfolios.

The factor loadings of our scaled joint strategy are similar to QMJ, except the SMB that becomes statistically insignificant from zero. We can infer that our portfolio holds more small firms than the normal QMJ. The excess returns are higher than the normal QMJ, and the Sharpe ratio is drastically higher in the dynamic portfolio. Although the momentum returns are the highest overall, the crash risk is mitigated in the joint strategies. Furthermore, we can infer that QMJ works as a natural hedge against market downturns.

We realize that using previous momentum returns as a weight function may not be the best way. In fact, we find that using market volatility gives similar gains in the Sharpe ratio. Furthermore, by reducing the time window and looking at previous months instead of three months back, we gain additional Sharpe ratio increases. As momentum is more volatile, target volatility also plays a role in determining the effectiveness of the hedge.

Regardless of target volatility, the joint strategies have lower volatility. However, the fact that a simple "crash-predictor" is enough for QMJ to work as a hedge against market crashes is intriguing. Our findings imply that QMJ can act as a complementary strategy as a risk-mitigation tool. This adds an additional challenge to the risk-based theories, suggesting that quality may be a pricing anomaly.

Table 6.1: Results with Scalar

This table shows the monthly excess return and factor loadings of the QMJ factor, WML, a strategy going 50/50 in WML and QMJ, and a strategy going into both strategies using a dynamic scalar. The sample period runs from July 1957 until June 2020. The QMJ factor is constructed at the intersection of six-value weighted portfolios formed on size and quality, refreshed and re-balanced monthly to sustain the value weights. The explanatory variables in the time-series are the returns of the market, size (SMB), book-to-market (HML), robust minus weak (RMW), and conservative minus aggressive (CMA). All factors, including WML, are downloaded through Kenneth French's data libraryFrench, K. (2021). The alphas and the excess returns are reported in monthly percent, and the t-statistics are presented in parentheses. Sharpe ratios are annualized.

	QMJ	WML	50/50	Scalar
Excess Returns	0.27	1.25	0.76	0.91
	(3.10)	(4.64)	(4.86)	(7.66)
CAPM-alpha	0.40	1.42	0.91	1.03
	(4.92)	(5.32)	(6.00)	(9.05)
3-Factor alpha	0.49	1.62	1.06	1.13
	(6.68)	(6.18)	(7.25)	(10.32)
5-factor alpha	0.31	1.38	0.85	0.96
	(5.09)	(5.17)	(5.84)	(9.03)
MKT	-0.19	-0.30	-0.25	-0.19
	(-12.49)	(-4.61)	(-6.89)	(-7.17)
SMB	-0.08	0.02	-0.03	-0.06
	(-3.60)	(0.25)	(-0.53)	(-1.72)
HML	-0.25	-0.82	-0.53	-0.31
	(-8.85)	(-6.59)	(-7.94)	(-6.24)
CMA	0.01	0.53	0.27	0.08
	(0.29)	(2.81)	(2.65)	(1.13)
RMW	0.55	0.40	0.48	0.49
	(18.71)	(3.10)	(6.81)	(9.48)
Sharpe Ratio	0.41	0.61	0.64	1.01

7 Discussion

In this chapter, we discuss the findings from chapters 4 and 5, and the implications of the results. Institutional investors invest on average more in quality and junk stocks than their respective market shares would suggest. One possible explanation to these results is that smaller investors do not diversify as much as larger funds. It is reasonable to assume, as the data shows that most institutional investors are smaller funds.

The plot in figure 4.1 suggests that the market share of junk stocks is in a downward trend. This implies that investors invest more in junk stocks in recent years. Furthermore, the second plot in figure 4.3 suggests that the trend is not reversed during recessions and the regression on change in junk ratio shows no evidence of a flight from junk. These findings are not intuitive as junk stocks are, per definition, the least profitable, safe, and slowest growing firms, and investors seem to remain invested in junk stocks during recessions. One explanation might stem from behavioral finance, where some investors hold on to losing investments too long, called "the disposition effect" (Barberis and Xiong, 2006) or so-called "anchoring" where investors do not sell their investments until it reaches the initial price or above (Tversky and Kahneman, 1974). This effect makes it less likely that investors sell a stock that has been going down than up. In general, the recession fails to explain part of the change in the junk ratio.

In general, investors seem to have a higher appetite for risk during expansions and become risk-averse during recessions. Although this can give a rational explanation as to why investors would prefer quality stocks during recessions, it does not explain why investors would not leave junk stocks. Junk stocks are more volatile than the market and perform poorly during recessions. Furthermore, the high abnormal QMJ returns during recessions come from shorting junk stocks. If investors move into quality but do not leave junk, they must sell other, unidentified stocks. This is puzzling, as it is not clear which stocks the investors would prefer to sell over junk stocks. One possible explanation could be that the junk stocks lose too much of their value during recessions and that institutional investors prefer to sell other stocks not to realize the loss. That would imply another behavioural explanation.

Our findings from section 5.3 suggest that investors flee to quality but look for more than only safety. Although this does not reject the idea that investors flee to safer assets, this finding gives some nuance to the topic. Much of the previous literature use safer asset classes like treasury bonds to test the *flight to quality*. However, maybe investors are chasing something else in the equity markets. It is reasonable to assume that investors chase higher returns in the equity markets. Despite being more risk-averse during recessions, a higher expected return can increase the utility of the investor.

Looking further at the notion of *flight to quality*, it seems like institutional investors favour and invest more in quality stocks during recessions. We can infer that there is a *flight to quality*. However, we cannot conclude it, as a *flight to quality* would imply that investors seek quality during recessions and flee low-quality assets. We do not find evidence that investors leave low-quality stocks. Bernanke et al. (1996) find evidence that "less-safe" firms do not have access to credit to the same extent as safer firms during market distress, implying that the low-quality stocks are riskier during recessions. The volatility of junk stocks is higher than the market volatility, QMJ, and quality stocks, suggesting that junk stocks are riskier during recessions. Thus, it is difficult to give a rational explanation for not leaving junk stocks.

Another problem is that the performance of quality stocks cannot be directly attributed to the *flight to quality*. It is unclear whether the quality stocks perform well because of investor herding or if investors herd to quality stocks because they perform well. Further, investors may not be aware of or look for the quality factors in a firm.

Vayanos (2004) finds that investors' liquidity premia increases during recessions and Beber et al. (2008) find that investors flee to liquidity rather than credit quality. Both studies discuss the preference of liquidity during recessions. One possible explanation for favouring quality firms is that they are more liquid than other firms and that investors do not flee to *quality*, instead prefer quality stocks because of endogenous characteristics. It is beyond the scope of our thesis to test the endogenous characteristics of quality and junk stocks. However, this could explain why quality stocks see increased demand from institutional investors during recessions and can be a topic for future research.

8 Conclusion

In this thesis, we test whether institutional investors flee to quality within equity markets during recessions. Earlier financial literature that tests for *flight to quality* focuses mainly on the flight from equity markets to safer asset classes such as treasury bonds. Using the quality definition by Asness et al. (2019) and 13f-filings, we find evidence of flight to quality during recessions within the US equity market. The findings are robust to adjustments of the market share of quality stocks, suggesting that the flight is deliberate. The results suggest that the *flight to quality* is not attributed to the safety component of quality alone, suggesting that investors do not only look at the safety characteristics of a stock. Furthermore, it is not clear whether quality stocks outperform because of the *flight to quality* or if investors herd to quality stocks because they outperform.

The highly positive abnormal returns QMJ generates during recessions derive from shorting junk stocks. We find no evidence to support that institutional investors leave junk stocks during recessions, implying that they sell other, unidentified stocks. Although a flight to quality can be rational, there is no rational explanation for not leaving risky, unprofitable, highly-leveraged, and bankruptcy-prone firms during recessions. This opens up for future research where behavioral factors and endogenous characteristics of quality and junk firms are investigated as potential explanations.

In the last part, we test whether the QMJ strategy can be used as risk-mitigation and enhance the WML strategy. By creating a QMJ-WML joint-strategy portfolio with an arbitrary 50/50 weight scheme, the Sharpe ratio of both strategies increase. By scaling the portfolio weights to go more into QMJ during high-volatility environments and go more into WML during low-volatility environment, the Sharpe ratio increases further and the momentum crash risk is mitigated. In short, QMJ can be used to mitigate the crash risks of momentum.

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Appendix

A Appendix A: Formulas for Replicating QMJ

A1 Accounting Variables

$$\begin{aligned} Working\ capital = {} & Current\ assets - Current\ liabilities + Short\ term\ debt \\ & - Cash\ and\ short\ term\ instruments + Income\ taxes\ payable \end{aligned} \tag{A.1}$$

$$Book\ equity = Shareholders'\ equity - Preferred\ stock \tag{A.2}$$

Notes on adjustments in data:

- Preferred stock is equal to PSTKRV, PSTKL, or PSTK, depending on availability, in that order.
- If shareholders' equity is missing, we replace it with (Common equity + Preferred stock) or (Total assets - Minority interest - Total liability), in that order.
- If Debt in current liabilities is missing, we impute it by taking the sum of Long-term debt due in one year and Notes payable.
- If Current liabilities is missing, we impute it with the sum of Accounts payable, Debt in current liabilities, Taxes payable, and Other total current liabilities.
- If the Total liabilities is missing, we impute it by taking the sum of Current liabilities, Deferred taxes and investment credit, Total long-term debt, and Other total liabilities.
- If the Total current assets is missing, we impute it by taking the sum of Cash and short-term investments, Total inventories, Total receivables, and Other total current assets.

A2 Profitability

$$GPOA = \frac{Total\ revenue - Cost\ of\ goods\ sold}{Total\ assets} \tag{A.3}$$

$$ROE = \frac{Net\ income}{Book\ equity} \tag{A.4}$$

$$ROA = \frac{Net\ income}{Total\ assets} \tag{A.5}$$

$$CFOA = \frac{Net\ income + Depreciation - \Delta Working\ capital - Capital\ expenditures}{Total\ assets} \tag{A.6}$$

$$GMAR = \frac{Total\ revenue - Cost\ of\ goods\ sold}{Total\ sales} \tag{A.7}$$

$$ACC = \frac{Depreciation - \Delta Working\ capital}{Total\ assets} \tag{A.8}$$

A3 Growth

$$\Delta gpoa = \frac{gp_t - rf * at_{t-1} - (gp_{t-5} - rf * at_{t-6})}{at_{t-5}} \tag{A.9}$$

$$\Delta roe = \frac{ib_t - rf * be_{t-1} - (ib_{t-5} - rf * be_{t-6})}{be_{t-5}} \tag{A.10}$$

$$\Delta roe = \frac{ib_t - rf * at_{t-1} - (ib_{t-5} - rf * at_{t-6})}{at_{t-5}} \tag{A.11}$$

$$\Delta cfoa = \frac{cf_t - rf * at_{t-1} - (cf_{t-5} - rf * at_{t-6})}{at_{t-5}} \tag{A.12}$$

$$\Delta gmar = \frac{gp_t - gp_{t-5}}{sale_{t-5}} \tag{A.13}$$

Notes:

- All accounting variables are divided by the common shares outstanding (CSHO). To distinguish the difference, all variables are lowercase.
- Residual income is calculated by subtracting profits the firm would have incurred if it invested its total assets at the risk-free rate the year before.
- If there was no available data available about a firm's Total assets the previous year, residual income is assumed to be 0.

A4 Safety

$$LEV = -\frac{Long\ term\ debt + Short\ term\ debt + Minority\ interest + Preferred\ stock}{Total\ assets} \tag{A.14}$$

$$Beta = -\beta_i = -\frac{\sigma_i}{\sigma_m}\rho \tag{A.15}$$

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

$$\begin{aligned} Ohlson's\ O-score = &-(-1.32 - 0.407 * log(ADJASSET/CPI) \\ &+ 6.03 * TLTA - 1.43 * WCTA + 0.076 * CLA - 1.72 * OENEG \\ &- 2.37 * NITA - 1.83 * FUTL + 0.285 * INTWO - 0.521 * CHIN) \end{aligned} \tag{A.16}$$

Where:

- $ADJASSETS = Total\ assets + 0.1 * (Market\ equity - Book\ equity)$
- $CPI = Consumer\ price\ index)$
- $TLTA = Book\ value\ of\ debt/ADJASSETS$

- $WCTA = (Current\ assets - Current\ liabilities)/ADJASSETS$
- $CLCA = Current\ liabilities/Current\ assets$
- $NITA = Net\ income/Total\ assets$
- FUTL = Pre-tax income /Total liabilities.
- OENEG is a dummy equal to one if the total liabilities exceed total assets.
- INTWO is a dummy equal to one if the net income is negative for the current and prior fiscal year.

$$Altman's\ Z - score = \frac{1.2WC + 1.4RE + 3.3EBIT + SALE}{AT} + \frac{0.6ME}{LT} \quad \text{(A.17)}$$

EVOL is the standard deviation of quarterly ROE over the past 60 quarters. We require 12 non-missing quarters and annualize the volatility. If we miss quarterly data, we require at least five non-missing fiscal years of data and use the annual ROE over the past five years.

B Appendix B: List of Variables

Here are the variable from Compustat and CRSP presented, which is used in this thesis. The names are abbreviations, which is identical to the variable abbreviation found in the databases.

COMPUSTAT

Type: Quarterly and yearly

Time Range: June 1950 to June 2020

Table A0.1: Compustat Variables

GVKEY	DATE	FYEAR	ACO	ACT	AP	AT
CAPX	CEQ	CH	CHE	COGS	DD1	DLC
DLTT	DP	DVP	EBIT	DP	IB	IDIT
INTPN	INVT	LCO	LCT	LO	LT	MIB
MIBT	NI	NP	PI	PSTK	PSTKL	PSTKRV
RE	RECT	REVT	SALE	SEQ	TXDITC	TXP
TXT	XINT	XOPR	EXCHG	SIC	ATQ	CEQQ
IBQ	LTQ	MIBQ	PSTKQ	SEQQ		

CRSP

Type: Monthly and daily

Time Range: June 1950 to June 2020

Table A0.2: CRSP Variables

DATE	SHRCD	EXCHCD	SHRCLS
DLSTCD	DLRET	PRC	RET
SHROUT	VWRETD	PERMNO	SICCD

C Appendix C: Replication of Barroso and Santa-Clara

Table A0.1: Replication of Barroso and Santa-Clara Scalar

Replication of Barosso and Santa-Clara (2015), table 3, excluding the information ratio. Reported are the annualized excess returns and standard deviation in percentages, kurtosis, skewness, and Sharpe ratio for the plain momentum (WML) and risk-managed momentum (WML*). The risk-managed momentum (WML*) uses the realized variance of the portfolio in the previous six months to scale the exposure to momentum (WML). The first two rows represent a replication of the table using data obtained from the original paper. The original data uses monthly WML portfolio returns from March 1927 to December 2011 and daily WML portfolio returns from August 1926 to December 2011. The last two rows represent a replication of the table following the procedure outlined in the original paper. The daily WML portfolio returns are obtained from Kent Daniel from January 1927 to July 1963 and from Kenneth French's library from July 1963 to December 2011. The monthly WML portfolio returns are from Kenneth French's library from July 1927 to December 2011.

	Max	Min	Mean	Std. Dev.	Kurtosis	Skewness	Sharpe
WML Orig.	26.180	−78.960	14.460	27.530	18.330	−2.470	0.530
WML∗ Orig.	21.950	−28.400	16.500	16.950	2.690	−0.420	0.970
WML Rep	26.140	−77.020	14.610	27.420	17.760	−2.410	0.530
WML∗ Rep	21.740	−27.700	16.580	16.830	2.400	−0.380	0.990