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EFFECT OF FINANCIAL CRISIS ON FF5 RISK-FACTORS

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ABSTRACT OF THE MASTER'S THESIS

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Abstract

This thesis gives an overview of the research that has been conducted studying major risk-factors (size, value, profitability, momentum, investments) and Fama-French asset pricing models. Aim of this thesis is to study changes in major risk factors at the U.S. equity markets after the global financial crisis. The empirical part of this thesis uses three 120-month periods of daily data, focusing mainly on changes between the 120 months before and after the global financial crisis using the end of 2008 as a breakpoint for data. Also, the performance of the Fama-French five-factor model is evaluated in three different periods, revealing information on how the model works with various samples of data.

Research set up follows mainly similar approach as in Fama and French asset-pricing studies by using portfolio sorts of different characteristics and portfolios that mimic risk factor returns. This thesis adds to the existing literature by evaluating three short periods of 120-months and comparing relative changes on these periods. The main focus is comparing risk-factor coefficients, risk factor return patterns, and performance of the Fama-French five-factor model in (01/1999 – 12/2008) data sample to (01/2009 – 12/2018) data sample in the U.S. equity market. The third period is used to control and point the magnitude of changes after the financial crisis.

Results of the empirical part of this thesis reveal significant differences in risk-factors after the financial crisis. Previously discovered risk-factor return patterns disappear in the period after the financial crisis. This change is significant as clear and strong patterns of risks factor effects in average returns can be seen in the first two periods. Regression tests reveal clear trends in risk-factors coefficients. Profitability factor obtains explanatory power (importance) coming to the present day as the value factor loses explanatory power. Size factor gains on small firms’ categories but loses on big-sized firms. Investment factor does not play a significant part in explaining returns in general in the period after the financial crisis. Fama-French five-factor model performance is persistently highest in the period after the financial crisis supporting its usage on different applications.

Main findings show enhanced importance of profitability factor. This signs of the increased importance of quality characteristics of firms in explaining the excess returns in line with recent quality-based studies.

Keywords
Risk factors, Asset pricing models, Fama-French, Market states, Financial crisis

Additional information

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1 INTRODUCTION

There have been significant changes in economic macro-environment in the last ten years. Changes include the global financial crisis, major changes in policy and long-lasting period of low-interest rates. The motivation of this study is to examine how the global financial crisis and the following changes in the economy have affected the most well-known risk-factors in the United States (later the U.S.) equity markets. To effectively limit the study, the focus is mainly on the Fama-French five-factor model (later FF5) and four different sorts of stocks to study this issue.

Financial markets have been outgoing major changes in the last ten years mainly because of the global financial crisis that happened around 2008. Regulators have noticed that equity markets need to be readjusted and regulated differently to effectively avoid such crises. The global financial crisis was a huge problem for the whole world economy resulting in low and negative rates of gross domestic growth and making the lives of millions of people harder. A so-called new era in the financial markets began after the global financial crisis and started the long reconstruction of financial markets. Changes introduced to markets are well visible today. This thesis examines how these changes in the financial markets have affected the most well-known firm-level risk factors such as value, size, profitability, and investments. There is a huge number of identified risk factors in the global equity markets, but risk-factors are mainly overlapping with each other. Thus, this thesis limits the focus on the most well-known risk factors, and the empirical part tests the Fama-French five-factor model in three different periods of 120-months with differently sorted portfolios.

This thesis adds to the existing literature by directly evaluating changes in risk-factor and Fama-French model performance on three relatively short periods. The main focus is on 120-months before and 120-month after the breakpoint which is the end of the year 2008. The bankruptcy of Lehman Brothers investment bank happened on 9. September 2008 which really started the global effects of this crisis. The control period/period one (01/1989 – 12/1998) is used to control and point out the magnitude of changes between the period two (120-months before the breakpoint) and the period three (120-months after the breakpoint). Daily data is used in most of the tests which result in more accurate estimates of movements of risk-factors. Those adjustments result in a different research approach than used in previous studies. Thus, this thesis adds important empirical evidence on the view of research on risk-factors, asset pricing models, and model applications.

Two research questions are following:

1. Effect of financial crisis on risk-factors on U.S. equity market
2. Steadiness of performance of FF5 on three short periods

The first research question is interested in the evaluation of the changes between the 120-month periods in the risk-factors on the U.S. equity market. To find answers to this question wide literature review on the issue is conducted and main findings introduced in this thesis. The empirical part evaluates the return patterns on differently sorted portfolios that mimic effects that risk-factors should have on average returns. Focus is on what are the differences in the return patterns before and after the financial crisis. Also, multiple regressions are conducted with the Fama-French five-factor model which shows the changing trends around the risk-factors as the outcomes of the regression tests. Second research question evaluates the performance of the Fama-French five-factor model in those regression test with different statistics. It has been shown that performance is high at in-sample data and out-sample data in the previous studies. This fact supports using this model to study questions related to risk-factors and asset pricing models. But there are no reported results on evaluating different periods on the in-sample data with the shorter periods on high frequently daily data. Different statics answers to question how steady the performance between periods is and can Fama-French five-factor model be reliably used on different asset pricing applications no matter the period.

Hypotheses:

1. There are significant changes in risk-factor after the financial crisis
2. Performance of FF5 model is affected by different states on market
3. Visible patterns on returns have changed because of the financial crisis
4. There is flight to quality after the financial crisis

The hypotheses to be tested are built on what is expected to be the results based on the literature review and the new market environment. Hypothesis strongly supports answering the research questions and they are evaluated mostly in conclusions chapter.

Research methods in this thesis include a literature review on previous empirical studies that study risk-factors and asset pricing models. On the field of risk-factors and asset pricing models, there is a large number of studies and this thesis is mainly focusing on the ground-breaking work by the authors Fama and French on the thirty-year-long period. Also, many of the most important studies and discussion on the risk-factors and models are brought up to back up the story. A short introduction to macro-finance and recap what happened in the financial crisis is also provided at the beginning of this thesis to introduce the reader to the topic. The empirical part follows a similar set up as used in the Fama-French studies but using daily data and relatively much shorter periods. The empirical part will use returns of the 5x5 and 2x4x4 sorted portfolios on different characteristics and returns of risk-factor mimic portfolios to study research questions. The empirical part will report the results and statistics of every 321 regressions made to these different portfolio sorts. The analysis discusses the differences visible between three periods, focusing mainly on the changes before and after 2008. Anchoring hypotheses on earlier literature, using publicly available data similar as in Fama and French studies with a large number of observations, and four different portfolio sorts leads to robust research set up on this thesis confirming that findings of this thesis are not related to other than real changes in the risk factors, state variables and the U.S. equity markets in general.

The empirical part of this thesis reveals that there are significant changes in risk-factors after the financial crisis. Those changes are higher in magnitude than changes between the control period and period two. Hypothesis one is strongly supported by the results shown in the evaluation of returns pattern between the periods and as the outcomes from regression tests revealing that risk factors have changed significantly after the global financial crisis starting around 2008. Hypothesis three that anticipates changes in risk factor return patterns is firmly accepted. Return patters show support to risk factor effects in the first two periods evaluated. Coming to the period after the financial crisis return patterns disappear in all cases, except for mild patterns in investment effect. Return dispersion is significantly lower in the last period than in the first two periods. All average returns seem to be similar no matter the differences in firm characteristics. Results from two-variate sort portfolios show that the differentiation of firms in the period after the financial crisis with risk factors evaluated in this thesis (value, profitability, investments) won't show return patterns that are discovered in previous empirical studies. On three-variate sorts, profitability can generate return patterns as anticipated by previous studies. These sorts show that more profitable firms generate higher average returns in all periods supporting the importance of profitability. The size effect, higher average returns of small firms is visible only in the second period at two variate sorts. On three-variate sorts dividing firms only on two size categories shows the size effect also in the period after the financial crisis.

There are clear trends in the risk factors shown by regression tests. Profitability factor gains explanatory power (importance) through the period increasing around five percentage in explanation power after the financial crisis. Value factor loses power through periods and decreases approximately the same amount in explanation power as profitability factor gains. Nearly suggesting shifts in power between these factors. Three-variate sorts confirm these findings and point out the increased importance of profitability factor in explaining the average returns on the equity market. Investment factor does not play an important part in explaining returns in general, excluding the extremely high and low investing firms and some expectations. Size factor gains explanatory power in small firms and decreases closer to zero in explaining returns of big firms. This signs of the increased illiquidity premium in markets after the financial crisis. Performance of FF5 in explaining average excess returns is persistently highest on the period after the financial crisis in all tests confirming the second hypothesis and supporting usage of FF5 in applications as it delivers high performance (around 95 %).

Chapter two shortly introduces the macro-finance and recaps what happened during the global financial crisis and examines how the market has evolved in the last ten years. The third chapter introduces risk-factors, several interesting findings, and consensus understanding of the risk-factors on equity markets. The fourth chapter introduces the asset pricing models and precisely helps the reader to become familiar with the Fama-French asset pricing models. The fifth chapter is the empirical part of this study that presents outcomes of tests and other related information, analyzing the changes between different periods. The sixth chapter concludes.

2 FINANCIAL CRISIS AND CHANGES IN MACRO-ENVIRONMENT

In this study, we are going to take focus on what kind of risk factors participants in U.S stock markets are willing to carry in different economic states of nature using the financial crisis and end of 2008 as a breakpoint. This chapter is a short introduction to the macro-finance and how it sees the pricing of assets at different market states. Macro-finance should help the reader to understand the situation this thesis is studying. The second part of this chapter is a short recap of what happened in the global financial crisis starting around 2008 and what changes have been introduced to the financial markets after the crisis. The thesis focuses on the changes that could be important in determining the changes in risk factors.

2.1 Macro Finance

It has been shown that different economic states of nature are correlated with stock prices. In good states of nature expected returns are low and in bad states expected returns are high. Those expected returns follow the longer anticipated state of the economy, called as business-cycles. (Fama & French, 1989) Fact is similar, but opposite with interest rates. In good times interest rates are high to slow down the economy and vice versa, interest rates are low in bad times to boost the economy. Macro-finance studies the link between asset prices and fluctuations in economic states. When studying different market states focus should not be concentrated on interest rates and consumption substitution, rather focus should be centralized on time-varying risk premiums and markets ability to carry risk in different states of nature. Thus, many macro-finance models focus on the idea that markets can carry more risk in good times than in bad times. (Cochrane, 2017)

Cochrane (2017) asses the question that seems to be simple; as equity premiums are much higher in the bad states of nature, why less amount of people are willing to hold stocks? However, the answer is not straightforward at all. The simple answer could be that stocks are risky, but that is not a complete answer. People are willing to carry risks in other areas of life, but why stocks are avoided in many cases? Answer must lie in somewhere that stocks carry different kind of risk, the risk that will hit at the worst times possible, and thus this risk is avoided. Times, when people avoid the risk of stocks, is in the times of recession. Losing savings in the stock market at the same time as losing a job may introduce risk that most people are not willing to carry. This would be too much of a shock to consumption on most individuals as people on average prefer smooth stream of consumption. Thus, this fear results in the fact that stock prices are low and risk premiums high across asset classes in the bottoms of the recession. (Cochrane, 2017)

Cochrane also points out an explanation that people come more risk-averse when there are no losses in good times, strengthening the recession effect on stock prices. Recessions seem to combine these two mindsets, fear and the increased risk-aversion that cause people to avoid stocks. Recessions are phenomena of markets lower capacity to carry risk, which results in increased risk-premiums and shift investors to change riskier assets to lower-risk assets. This shift is also called a flight to quality that happens during recessions. (Cochrane, 2017) Global financial crisis starting around 2008 in the U.S. subprime markets launched a recession that lasted very long and introduced the new kind of era in the financial markets.

2.2 Global Financial Crisis

The global financial crisis started around 2008 at the subprime mortgage market in the U.S. with reckless actions of financial institutions and market participants. The definition and the common view of the financial crisis are that problems in financial markets rise to the level that they affect the whole economy due to lack of flows of credit to households and businesses and this disruption is affecting the real flows of goods and services (Ovanhouser, 2009, p.1). The crisis spread from the subprime mortgage markets to different areas of U.S. financial markets and later to the whole world economy through the financial institutions. Markets were unstable already in 2008. And one starting point to the global spread of financial crisis can be seen the bankruptcy of Lehman Brothers in 15. September 2008, which spread distrust widely all over the financial markets. Nobody knew which counterparties had bad instruments or derivates in their balance sheet. This led to a sharp price in short term interest rates.

The global financial crisis started after a long period of success that had lasted sixteen years straight. Problems in financial markets had been effectively handled by central banks, and major hits to the economy were avoided (Ovanhouser, 2009 pp. 1-2). This success supported the trust in the economy and likely aided loosen credit giving. Governments failed in the regulation of financial institutions, and this allowed them to build a house of cards that would collapse eventually. Government activities were also likely strengthening the impact of the crisis, as they run large deficits on the public sector and were heavily in debt coming to 2008. Grant and Wilson (2012) also point out Chinese government activities as one reason for the oversupply of easy credit. Chinese government kept buying U.S. treasury bonds and to hold their currency value low. This likely aided crisis to form. (Grant & Wilson, 2012 pp. 1-2)

Central bankers and Federal Reserve (FED) were aware of problems in the subprime mortgage market, but those institutions could not anticipate that problems in subprime markets would widen to affect the whole financial system. Many losses occurring in markets during the crisis were caused by a similar setup as following; use of complex, speculative, and hard-to-value financial instruments that were bought with loan money. Then major financial institutions used different entities to remove those investments of their balance sheets. House of cards has been built on the markets that would collapse. Traditional tools to revive the economy from the crisis had been introduced by FED by lowering the interest rate and injecting the billions of cash to create liquidity in the markets to keep credit flowing. (Ovanhouser, 2009. pp 1-3)

The global financial crisis has been a disaster for millions of people who have lost their jobs, homes and savings (Grant & Wilson, 2012 pp. 1-2). Social costs of the financial crisis were large enough to warrant that the new restrictions on the markets need to be designed to lower the possibility of reckless trading activities that could hit the whole financial system and the real economy. (Ovanhouser, 2009)

2.3 New Rules in Financial Markets

The financial crisis was a huge disaster for the whole economy, which led to many regulators question where the old rules in the markets still apply or whether there is a need to design new ones. Calomiris (2011) points out that a successful start of the reform of financial markets must begin with identifying the flaws in policy and regulation that have existed for a long period. These flaws must be addressed and corrected if we want to avoid crises in the future. Government policies which allowed risk-taking activities of financial institutions were crucial in the development of the crisis. (Calomiris, 2011 pp. 73-91; Kaufman, Evanoff, Demirguc-Kunt, & Federal Reserve Bank, of Chicago, 2011)

Financial and macroeconomic questions have been too far away from each for a long time. Policymakers have noticed the need to adjust politics to bring these two more close to each other and intersect possible problems with financial factors and the real economy. Although this task is not easy, the better policy requires better analysis, and this lags much behind. (Borio & Drehmann, 2009; Kaufman et al. 2011) Building a more robust global financial regulatory and supervisory framework would be a good start. This could be done by moving towards common rules and greater international co-operation between central banks and governments. Reducing complex regulatory settlements in the financial supervisory and enchanting role of central banks in macroprudential supervision. (Orphanides, 2011, pp. 305-314; Kaufman et al. 2011)

2.3.1 Capital standards and liquidity

Higher capital standards for financial institutions would help to avoid future crises, as the lack of capital was one root reason for the crisis. Reasonable increases in capital standards would decrease risks without undermining the ability of banks to provide financial services and credit. Increased capital requirements are an important step toward a more stable financial sector. (Baily & Elliott, 2011 pp. 59-71; Kaufman et al. 2011) Liquidity problems did strengthen the impact of the crisis. After the Lehman Brothers bankruptcy financial institutions increased their cash reserves, which led equity markets to dry up. There was a possibility that the whole international monetary system would collapse, but that collapse was avoided by successful actions of governments and central banks in short-term crisis management.

The globalisation of finance did widen domestic liquidity problems to the international context. International liquidity trusted on ad hoc actions by FED in 2008, and there were inadequacies in the normal management of international liquidity. FED acted as last resort loaner for international liquidity and prevented bank failures. The crisis would have been much worse if there weren’t these emergency provisions of international liquidity by FED. To prevent future liquidity problems such as, Basel three programme was designed to regulate financial institutions minimum capital requirements, and it was the first internationally agreed program. (Allen, 2013)

After the global financial crisis, there is a need for better management of possible rising crises. Financial crises in different periods have been giving hints of themselves before they really broke out. Governments and regulatory bodies should deal with systematic risk and sources of financial vulnerabilities before it reaches critical points. Meaning creating new stability and regulation surveillance in the markets. Financial Stability Board has taken this task, which requires the U.S to make strong political commitments to national and international financial stability regulation. (Kawai & Pomerleano, 2011 pp. 127-153; Kaufman et al. 2011)

2.3.2 Changes in world economy

The crisis had led to shifts on power at world economy. Kirshner (2014) argues there is a diffusion of the economic power of the U.S in the leader of the world economy and the dollar’s role in the world currency. The dollar will certainly stay first among equals, but its role will decrease from previous. Kirshner anticipates that there will be more pressure for adjustments, new macroeconomic vulnerabilities and state of mind that the U.S. is not free of crises after all. New constraints, frustrations and vulnerabilities will lead eventually to the reassessment of U.S engagement with the surrounding world. (Kirshner, 2014) These proposed adjustments and changes have been seen in the financial markets over the last ten years. Interest rates have been historically low for a long time, and central banks have been injecting huge amounts of money to financial markets to keep them stabilized. Regulation has taken a shift towards more regulated and supervised markets. There are capital requirements for banks, different reporting needs about holdings, and other kinds of adjustments. One hint about new policies in the starting point of crisis from the government side was the failure of Lehman Brothers. The government showed that even one of the biggest is not too big to fail to reduce the moral hazard problem. The aim of policy and regulation is towards reducing the reckless actions of financial institutions and to avoid future crises in financial markets that hit the whole real economy.

3 RISK FACTORS IN EQUITY MARKETS

The global risk factor has a common structure among returns around different asset classes and markets. These return patterns are not really related to standard macro-level factors. Risk factors can be intercepted as characteristics of an asset, the main drivers behind return premiums. Different characteristics, risks, carry different risk premiums. If assets are priced rationally, the return of an asset is the sum of exposures to different risk factors. Normally returns have something that we are not able to explain with common risk factors, and this fact motivates to seek out for new risk factors or sources that drive asset returns. There is a large number of identified risk factors on equity markets, but many risk factors are correlated with each other and follow the patterns of the most important risk factors. Most important risk factors to explain returns on equity markets can be identified as the market return, size, value, momentum, volatility, profitability and investments. In this chapter, these risk-factors are discussed alongside with anomaly returns patterns found in the equity markets.

3.1 Market and Size

The market risk factor is different from other risk factors discussed in this chapter. In the big picture, it is affecting in returns of all assets with the positive or negative correlation to return. In many cases, a negative correlation is preferred to gain diversification benefits and sometimes this is the opposite. Thus, it really does not tell us much on return differences, moreover how much the asset follows the average return on of the market. The market factor is more important in asset pricing models than in straight differentiation and pricing of assets. The market factor is the return from the market minus the risk-free rate, meaning the excess return market can generate in a given period compared to riskless investment. The market factor is included in almost all asset pricing models as market return tend to have high explanatory power in the return of stocks. Market factor has been accused of being biased because it really is not able to describe real market return. This is because there is no possible way to create a market portfolio that contains all the assets in the market and discovers their excess return compared to the risk-free rate. The factor is normally build using the market return from the same or similar market where the asset we want to explain is traded. Although of possible biases, the market factor is widely used and leaving it out will significantly lower the explanatory power of asset pricing models. Asset pricing models are discussed in more detail in chapter four.

In short terms, size effect means that small-sized firms have higher expected returns than big sized firms on average. Size is one of the main building blocks and an important factor in asset pricing models (Asness, Frazzini, Israel, Moskowitz, & Pedersen, 2018). Fama and French (1993) studied common risk factors in returns of stocks and bonds. They found that market factor, size, and book-to-market equity ratio (BE/ME) has high explanatory power of returns on U.S. stock market in cross-sectional tests and size factor having explanatory power in univariate regressions suggesting the presence of risk factor. After these findings, size has been accused of being an unimportant risk factor. This is because size tends to follow other risk factors, have historically weak and time-varying performance that is not strong in tests to international markets. Another problem for this risk factor is also that size effect is most visible in microcap stocks that represent only a small percentage of U.S. stock market value. However, Asness et al. (2018) show that size matters much more than it was previously thought when asset quality is controlled. Previously accounted problems disappear when regressions control for quality or junk characteristics of the firm. This means sorting firms by their quality characteristics, which reveal the lost size premium, that is not only concentrated on microcaps, is stable and robust around equity markets and industries. (Asness et al. 2018)

Size factors correlation to average returns is much clearer and more robust when controlling for quality characteristics of a firm. Quality is key and the most important factor when seeking for size premiums. Asness et al. find that large firms tend to be quality ones as small firms tend to be junk on average. Behavioural theories explain that small stocks have higher shorting costs and more disagreement in the market, which eventually leads them to be more likely overvalued than undervalued. But when quality is controlled, small quality stocks can outperform large quality stocks and same holds for junk stocks. Basic size effect suffers from size-quality composition effect, which has caused these problems to discover size effect before and controlling reveals and increases the size premium significantly. In their quality-based studies, Asness, Frazzini and Pedersen (2019) find that there is a higher price premium for quality in large stocks than for small stocks, which offers one explanation why small quality stocks outperform large quality stocks on average. Size effect seems to be related positively to illiquidity and negatively to quality. Size seems to have both side relation to these characteristics, although liquidity and quality are not strongly related to each other. These findings support the size premium being illiquidity premium even though there is no further connection found. Measures of liquidity and illiquidity are correlated and lower the size premium when controlled in tests. However, smaller but still significant size premium remains in returns. Those finding put size on a more equal footing to other major risk factors in markets. (Asness et al. 2018)

Main metrics to evaluate firm size is the total market capitalization which tells the market value of equity, enterprise value, the book value of assets or different characteristics that describe relative size, for example, turnover.

3.2 Value and Quality

Value effect means that value firms have higher expected returns on average than growth firms. Fama and French (1992) find that average returns on U.S. stocks are positively related to the ratio of the assets book value of equity to assets market value of equity. Fama and French (1998) find similar results of associated value premiums in international tests to major and emerging markets. Findings suggest that value stocks seem to have higher returns than growth stocks around the markets on average. Value stocks have high ratios of book-equity to market-equity, earnings per price and cash flow per price. High BE/ME called as value stocks provide higher average returns compared to stocks that have lower BE/ME that are called growth stocks. Capital asset pricing model fails to explain the value premium effect in 1963 – 2004 test period, and thus, it is seen as an anomaly based on CAPM. (Fama & French, 2006) This return difference is called value effect or value premium.

To identify the value effect as a global risk factor, there needs to be a strong common pattern across asset classes and markets. Asness, Moskowitz & Pedersen (2013) show strong common structure among returns and significant return premium in value-based investment strategies. Value effect can only slightly be explained by macroeconomic variables such as business-cycle, consumption, and default risk. Main findings of Asness et. al was a co-movement pattern that is strong and holds in different asset classes, markets, and robustness checks. They also discovered that different value strategies are correlated across markets which suggest value as a common global risk factor. What causes value effect is still somewhat of a puzzle in asset pricing studies. A small fraction of value effect can be explained by value effects negative relation to liquidity risk. (Asness et al, 2013) One explanation to negative liquidity risk relation is that when there are bad states on markets and everyone is selling due liquidity needs or risk management, value stocks are not affected as much as conventional or highly traded stocks. (Pedersen, 2009) This fact offers one explanation for higher returns of value stocks compared to growth stocks.

Main metrics to evaluate the value effect of the stock is price-to-book ratio (P/B ratio) that is similar to BE/ME turned around as ME/BE ratio. P/B compares the current share price to book value per share. Higher the P/B ratio, higher is the market value of the firm's equity compared to equity's book value. Low P/B, among other ratios such as low P/E, can be seen as value stocks. High values of such ratios usually tell about the high growth prospects of a firm. This fact follows the naming of these two stock categories.

Quality effect means simply that higher-quality firms have higher expected returns on average than lower-quality firms. Quality has no universally accepted definition such as value effect has on academic literature. Asness, Frazzini & Pedersen (2019) define quality as an asset characteristic that investors are willing to pay more all-else-equal. Quality stocks have characteristics such as safeness, profitability, growth opportunities and good management behind the stock. Investors are willing to pay more for firms with high-quality characteristics, but still, the explanatory power of quality and its characteristic is limited on tests. It still remains as a question in asset pricing is quality effect an independent risk factor or is there some other risk factor behind it, that could improve the explanatory power. (Asness et. al, 2019)

To turn from value stocks to quality stocks, Novy-Marx (2013b) introduces the quality dimension of value. Quality investing is different from value investing. In quality investing, investors seek to find conventional firms with certain characteristics of quality and low price. Mainly quality and value strategies try to exploit similar goals, finding undervalued stocks in the equity markets. But value strategy exploits more of waiting for cheap enough price to buy a certain asset. Noxy-Marx points out that if an investor wants to exploit the full potential of value effect, the quality characteristics of the asset should not be left unconsidered. In quality investing both characteristics of an asset are important, quality and the price. This is due to the simple fact that cheap and profitable firms outperform firms that only carry one of these characteristics. In empirical tests, quality investing seems to outperform traditional value investing in a time of crises when traditional value strategies suffer drawdowns. (Novy-Marx, 2013b) Impact of quality can be seen as higher risk-adjusted returns from high-quality stocks. Excess return is consistent with the quality characteristics of stocks. Price of quality has varied around time, and in some states of nature, the market puts smaller or larger price premiums on quality characteristics of the firms. Cheap quality means that there are not as high price premiums associated with quality stocks. Large quality stocks seem also carry more price premium compared to smaller stocks creating size premium on small quality stocks. (Asness et al. 2019)

Drivers of quality excess returns are still to discover. There are suggestions that (i) quality stocks carry more risk than lower-quality stocks or that (ii) quality stocks are undervalued, and lower quality stocks overvalued. Risk explanation is not consistent with movements we have seen on equity markets, more the opposite. Flight to quality seems to favour and benefit high-quality stocks in bad states of nature, meaning they perform well in times of crises which challenges a risk-based explanation of quality premiums. It was also discovered that analysts seem to undervalue high-quality stocks and overvalue lower quality when comparing analyst estimates to realized returns on equity markets. This evidence shows some support to the second explanation of biased market valuation of quality stocks. No matter the reason for this effect, there is strong and consistent abnormal returns of quality factor in all robustness tests. (Asness et al. 2019) Findings of Novy-Marx and Asness et. al support the creation of the fourth hypothesis of this study; there is a flight to quality after the financial crisis. Looking for more support to this hypothesis, chapter five uses the global financial crisis as breakpoint to study changes in quality and other firm characteristics.

Many different metrics can be used to measure asset quality, such as Piotroski's (2000) F-Score that divides firms buy nine different quality characteristics. Each character is either a sign of good or low quality. Higher the score higher the quality of the asset.

Quality can also be studied, for example, by assets profitability, competitive advantages or accruals quality. As said before, there is no clear and universally accepted definition of what quality of asset really is.

3.3 Cross-sectional and Time-series Momentum

Momentum is a well-covered topic in academic literature. The simple idea behind momentum strategies is to build a portfolio that buys past winners and sells past losers. The investor holds this portfolio for three to twelve months to gain abnormal returns surrounding the momentum effect. Jegadeesh and Titman (1993) show that past winners portfolio gains significantly higher abnormal returns than a portfolio that contains past losers. Momentum effect lasts for three to the twelve months from the portfolio construction. This effect will reverse in the long run, and half of the excess returns from the winner portfolio will disappear in the 24 months. It is easy to understand where the name momentum comes from, the effect is like a short-run trend in equity markets. Based on Jegadeesh and Titman findings effect is not due to systematic risk exposures of assets or lead-lag effects. The momentum effect is consistent with the explanation of underreaction and delayed price response from equity markets to new firm-specific information. Thus, the first hints of momentum effect can be traced back to Ball and Brown (1968) accounting-based study that showed that there is a delayed market response to new firm-level information available. Transactions from investors who exploit momentum strategies and buys past winners and sells past losers move prices temporarily more away from their fundamentals. This results in stock prices to overreact to new information and make the momentum effect stronger. One explanation to momentum effect is also that people overreact to new short-term information and underreact to long-term information. (Jegadeesh & Titman, 1993)

Asness, Moskowitz and Pedersen (2013) discover that momentum strategies are correlated with other momentum strategies globally. There are only slight commons in momentum effect with movements in common macroeconomic variables such as consumption, business-cycle and default risk. Asness et al. find that value and momentum strategies are negatively correlated with each other, which can be explained by opposite exposures to liquidity risk. But liquidity risk only holds for partial explanation to momentum effect, leaving much unexplained. Momentum effect has positive exposure to liquidity risk that can be due trades that follow momentum strategy, as these trades represent the most popular trades in the market and there is more price pressure on them in bad states (Pedersen, 2009). Daniel and Moskowitz (2016) show that momentum strategies suffer from panic states in the market when volatility is high, and past losers have high return premiums. When the market starts to reverse from bad state momentum strategies will crash. This is because momentum strategies sort past losers, which there are many after the downwards market movement. The momentum effect is particularly reversed during bad states on the market. (Daniel & Moskowitz, 2006)

Thus, different market states affect the momentum effect. Cooper, Gutierrez Jr. and Hameed (2004) study whether momentum profits differ with market states. They found that profits from momentum strategies are greater following market gains by using lagged market returns to determine upwards and downwards markets. Short-run momentum effect excessively follows the market movements as a six-month momentum strategy in upwards market gains significant return around one percentage per month, and following downward markets strategy loses insignificant half percentage per month with robust tests. Long-run reversals from downward markets were also significant, although there was no initial momentum effect. This finding suggests that reversals are not solely due to corrections of prior momentum. Hence, the state of the market is a significant predictor of successfulness of momentum strategies. The profitability of momentum strategies increases as lagged market return increases. The conclusion is that asset pricing models need to incorporate market states in them. (Cooper et al. 2004)

Time-series momentum differs from cross-sectional momentum as time-series momentum focuses on a single asset and its past performance on a short period. Cross-sectional momentum focuses on assets that outperform their peers in the cross-sectional setup at three to twelve months and will continue to outperform their peers in the next month. Moskowitz, Ooi, and Pedersen (2012) find significant time-series momentum in 58 different financial instruments such as equity indexes, currency and different futures. The momentum effect is not only tied to equity markets based on those findings. Time-series momentum means that past 12-month performance is a strong and positive predictor of future performance considering a single asset on time-series data. This effect is consistent across different asset classes and markets. The common time-series pattern is supported by a stronger correlation between time-series momentum strategies than the asset classes themselves. Similar behaviour and patterns from different markets and instruments can be found at the same time by competently different types of investors. Time-series momentum effect lasts around one year, and there is persistence in returns for up to 12 months with substantial abnormal returns. After this period effect reverses on longer time horizons. These results are consistent with sentiments theories of under and overreaction, and there is only small exposure to standard asset pricing factors. Time-series momentum seems to perform best during extreme market conditions on their empirical tests. (Moskowitz et al. 2012)

Moskowitz et al. find that most of the time-series and cross-sectional momentum effect is driven by positive autocovariance to futures contracts. Time-series momentum captures the effect associated with cross-sectional setup, although they are built from a different set of securities. The finding indicates a strong correlation with these two momentum strategies even when they are applied to a competently different set of assets. This suggests that time-series momentum captures individual stock momentum. Time-series momentum effect is partly explained by trades of hedgers and speculators in the derivates markets. Speculators seem to load on average to time-series momentum and gain from it as long as the trend continues. Hedgers seem to take opposite sides on those trades and lose from time-series momentum effect. (Moskowitz et al. 2012) Thus, these finding on cross-sectional and time-series approach can be identified as part of the same phenomenon that results on some extend from the lagged market response, liquidity risk, and activities of market participants.

There are no straightforward metrics to evaluate the momentum of an asset. Momentum can be found out by dividing assets in different quantiles and separating past winners from losers or as in time-series approach looking for a 12-month track record of the asset. The magnitude of momentum effect is the difference in returns between those winner and loser quantiles in three, six to twelve months.

3.4 Beta and Variance

Beta means the coefficient and correlation of stock return against market return and beta one means that stock price moves perfectly hand-in-hand with the market. In the basics of capital asset pricing model lies the fact that high beta stocks should have higher returns compared to low beta stocks as they carry more risk and volatility. However, this is not the case always. The regression line is too flat, and the CAPM model fails to explain this variation between stocks with different levels of beta. Frazzini and Pedersen (2014) show that higher beta stocks have lower alpha than stocks with low beta. Alphas and Sharpe ratios lower systematically as asset beta increases and the phenomena is visible over the markets and asset classes. This suggests the global factor in returns. Frazzini and Pedersen create betting against beta factor to test this issue. BAB factor is used to create a portfolio that buys low beta assets with leverage and shorts the high beta assets. After this portfolio is leveraged back to the beta of one. BAB factor has significant risk-adjusted returns and is robust to several specifications in their empirical tests. (Frazzini & Pedersen, 2014)

Frazzini and Pedersen provide an explanation to this effect since there are different constraints in the real-world investors. These constraints are, for example, margin requirements and constraints to use leverage to buy assets. This result investors that face constraints to bid up prices of high beta assets following the lower alpha of these high beta stocks. Results are consistent with these explanations, and it can be seen directly from equity markets that more constrained investors hold riskier stocks. When market states variate, dispersion of betas are significantly lower as funding liquidity risk is high in a time of crises. This results betas to be pushed towards one. (Frazzini & Pedersen, 2014) As market state will affect funding liquidity risk, it is safe to conclude that BAB factor and this beta phenomenon is affected by different market states, resulting in higher returns in good states and lower in times of crises.

Cederburg and O’Doherty (2016) recommend that BAB factor and strategies exploding it should be viewed with caution. They show that accounting for time-series variation in betas and different state variables significantly reduces the return difference between high and low sorted beta portfolios. Using unconditional beta as in Frazzini and Pedersen study results in higher cap between beta sorted portfolios and alpha is a biased estimate of a true alpha. Using conditional beta is motivated by a large dispersion of firm-level beta in different states on the market. Beta variation is a result of different market risk premiums, volatility, investment opportunities, leverage, and idiosyncratic risk that variate as a result of market states. Beta caps variate highly between 95% and 5% quantile portfolios as in different states cap between portfolios has been from 1.5 to 3.0. Conditional process models beta as lagged state variables and macroeconomic variables. Conditional beta results in much lower insignificant alphas between portfolios of high and low beta. When comparing this result to the unconditional case, it is easily seen that the betting against beta phenomena is largely erased after taking these changes into account. Testing multifactor models such as Fama and French (1993) three-factor model with conditional modelling support this evidence. (Cederburg & O'Doherty, 2016)

Common knowledge is that market returns correspond negatively to variance shocks. This negative correlation between variables implies that the market is subject to variance risk. In times of high negative correlation between returns and variance, market returns are more predictable in short horizons with a variance risk premium. Pyun (2019) shows that market returns can be predicted in economically and statistically significant results in one-month periods, by using factor build from innovations to variance such as prices of options on equity indexes. Pyun argues that this factor can be used to predict different returns in short horizons that correlate highly with the equity market return. These findings are different from other factors as return predictability is normally weak in short periods (one to six months) using the common factors discussed before. The variance risk premium, however, can be used to predict short-horizon returns on equity and correlated markets at least in theory. (Pyun, 2019) Firm-level beta can be measured by regressing market return against stock return. Results are the estimate of alpha and beta of the firm. Stock beta is reported and used widely in financial markets and applications.

3.5 Profitability and Asset Growth

Profitability can be seen as a quality characteristic of a firm. Those effects are partly overlapping, but with profitability, more explanation power can be found on returns than with the quality factor. Fama and French (2006) find that after controlling for other variables such as BE/ME and investments, more profitable firms have higher expected returns than unprofitable firms. Profitable firms are referred to as firms with higher expected earnings relative to book equity. Findings of Novy-Marx (2013a) support these findings of Fama and French and show that gross-profitability measured by profits to assets (profitability ratio) generates significantly higher average returns when profitable and unprofitable firms are compared. This is true even to fact that those unprofitable firms having lower BE/ME, and higher market capitalizations. This effect is called cross-profitability premium. Profitability factor has approximately the same predictive power as the value factor has to cross-section tests of stock returns. Novy-Marx also discovered that profitability factor generates perfect hedge for value strategies as these strategies look for returns in opposite directions from value and growth firms. Profitability is on the other side of value. Investors demand higher returns from firms that are riskier, resulting in higher BE/ME ratios. The argument is similar to that productive firms where investor require higher average returns should be priced similarly to less profitable firms that investors look for lower returns. Productivity helps us identify this profitability factor leading to the fact that higher the required profitability higher the returns. This results in more profitable firms to generate higher average returns than similar unprofitable firms. (Novy-Marx, 2013a)

This profitability effect is typically thought as mispricing in markets, referring to irrational pricing of assets. Another explanation is based on rational pricing, and differences in risk as stocks with higher profitability and higher BE/ME are riskier, thus having higher average returns. What explanation is the right one is still not clear. (Fama & French, 2006) To find an answer to this question, Sun, Wei and Xie (2014) studied cross-sectional profitability on international equity markets and find similar gross-profitability premium than in U.S. based studies. Explanation to gross-profitability premium is in line with rational pricing, as in highly developed markets with low investment frictions effect is significantly stronger than in markets with high investment frictions. Explanations for irrational pricing of assets had no support based on findings from international markets. (Sun et al. 2014)

Investment effect means that low investing firms have higher expected returns on average than high investing firms. Fama and French (2006) show that higher expected rates of investment are associated with lower expected returns when controlling for other variables such as BE/ME and profitability. Assets growth relation to cross-sectional of stock returns has been studied mainly thought sub-components of growth. Cooper, Gulen and Schill (2008) take a new approach to study asset growth relation to stock return by studying firms aggregate asset growth's relation to returns. Asset growth ratio is measured by the percentage change in total assets, which captures complicated links between returns, size groups and financing types of different firms. Cooper et al. document strong cross-sectional predictive power and negative relation between asset growth and stock returns. The aggregate asset growth rate is a strong predictor for future abnormal returns, and it is common to many subcomponents that make total asset growth. Cooper et al. show that events that are associated with asset expansion such as mergers and acquisitions are followed by low abnormal returns and events following the asset contraction will result in high abnormal returns on average. Low growth firms can generate much higher returns than firms with high growth percentage in total assets. Spread with equally weighted data is large at 19.4 % percentage and with value-weighted data spread is 8.4% between low and high growth firms. (Cooper et al. 2008)

The market state has an effect on this phenomenon. Cooper et al. argue that lagged market states predict larger spread between low and high growth firms when managerial overconfident increases as market increases. Market increase and a larger number of lagged positive returns result in higher managerial overconfident and investor overreaction to high growth rate firms. These facts will lead to stronger mispricing between firms with high or low asset growth characteristics. A possible explanation for investor overreaction to high growth rate firms comes from agency theory as there are fears of overinvestment problems or empire-building susceptibility of management. (Cooper et al. 2008)

International evidence by Watabane, Xu, Yao and Yu (2013) supports Cooper et al. findings in the U.S stock market. Watabane et al. find a significant spread between high and low asset growth firms in value and equally weighted portfolios in robust tests. The relation is similar that found in U.S. markets that high asset growth rates predict low expected returns. More important were findings that the asset growth effect varies across countries studied. The return spread was in the range of -11% to 11% and was positive in thirty countries, but negative in thirteen countries. Watabane et al. show that the effect of asset growth is stronger in developed economies with more important and effective stock markets. Another explanation for asset growth effects such as limits to arbitrage, higher investor protectionism, and more quality accounting had only small explanatory power on asset growth effect in international tests. (Watabane et al. 2013)

Metrics to evaluate profitability is to use the procedure as in studies by calculating profitability ratio by dividing earnings by book value of assets. There are also many financial ratios such as operating profit margin, net profit margin to evaluate firm profitability. Firm growth can be measured by total asset growth or calculating the growth percentage of different parts of a financial statement.

3.6 Market States and Risk Factors

All these risk factors have been under a lot of discussion in the academic world. There are many opposite views with different research setups and market environments. Research discussing different risk factors existence and patterns are still going on, and much new evidence is discovered in recent years. What we can conclude based on the literature review is that all these risk factors will be affected in some way by different states in the markets and changes in funding liquidity risk seem to be the common factor behind changes in many risk factors patterns. Funding liquidity risk and liquidity are affected by different market states. As the market goes down, liquidity is weaker and when markets go up liquidity is higher. Those situations will eventually be reversed in tops and downs of business cycles with the help of government and automatic stabilizers.

Based on literature review value and quality risk-factors are not much affected by different states on the market. Trading strategies based on those risk-factors seem to perform consistently well in different market states in earlier empirical studies. Gathering steady returns quality of firm seems to be a more important factor than value as quality outperforms value in the downmarket environment. This effect is referred many times as “flight to quality” that happens when crises arise in markets. Everyone wants to buy the safest quality stocks that are thought to get the least hit from the crisis. This eventually leads assets that are characterised as quality to have steadier bid-ask spread through different market states and price is more stable.

Some risk-factor effects even seem to disappear and reverse in the downmarket as seen in case of momentum. This really gives a thought is this phenomenon really risk factors in equity markets or something else. But momentum crash is more since this trading strategy used in empirical studies buys past losers which there are many in downmarket compared to winners. The market tends to reverse in some horizon after the crises and lower the high return premiums from all stocks. If investors are betting on the short size on these situations its most surely going to be a loss. It is easy to assume that rational investors would not be shorting four out of five stocks strictly following the momentum strategy in long downmarket during recessions. This fact is again causing a momentum effect to lose power and reverse. Cross-sectional momentum is thus much stronger in the upmarket than in the downmarket. Interesting was that time-series momentum still seems to perform very well in extreme conditions.

Betting against beta factor and asset growth are also highly tied phenomena of upwards markets. In higher markets levels as betas and overconfident increases spreads between extreme portfolios increases in a significant manner. In down markets, these effects lose much of their power and spread decrease. Markets then reverse on time to time as valuations fall too far away from the firm fundamentals. So, it is interesting thought which market situation best describes the normal situation in markets? The time when valuations are far away from their fundamentals in up markets and investors are accepting lower return premiums. Or in downmarket when common structures that academics have found in returns are mainly weak, not very significant, and return premiums are high. It is also interesting what is the situation now in the equity markets, approximately eleven years after the beginning of the global financial crisis. The market seems not to still recover fully from this crisis as the financial market has characteristics of both up and down market with low-interest rates and high equity valuations.

It is also interesting that these common factor patterns to not have much return predictability in the short run tests. This may be because they do not follow macroeconomic changes very closely as stated in the definition of global risk factor. They reverse and settle with macroeconomic variables only at the longer run. Only the factor build from volatility innovations seems to have short-run predictability power on future market returns.

4 FAMA-FRENCH ASSET PRICING MODELS

There is a large number of asset pricing models that are built from the different risk factors discovered in the global financial markets. In chapter three, there was a discussion on these risk factors and very short introductions to the basics of asset pricing models. This chapter takes a more detailed look at asset pricing models focusing mainly on equity markets and ground-breaking work of Fama and French on thirty year-long period. The chapter also evaluates the performance of Fama-French models in different tests closely to understand models' weaknesses, areas of good performance and applications.

To start introducing asset pricing models first look should be taken to the very simplest one, the random walk model.

$$\textit{Random walk model,} \qquad E(P^t) = P^{t-1} + \in \tag{1}$$

Where $E(P^t)$ is expected price at time t, P^{t-1} is price at t-1 and $\in$ is error term.

Random walk model tells that asset price today is asset price yesterday and something random. Interpretation of this model reveals that it is not possible to predict future asset prices based on historical return data. There is always a random component in the model that could not be predicted. Best guess for tomorrow's price is that it is the same as price today. But this is not the whole case at least in the longer run, there should be some predictability on the returns of assets. Most well-known asset pricing model is the capital asset pricing model by Sharpe (1964) and Lintner (1965) which was one driver to start a large amount of academic literature and applications to different asset pricing models which try to explain common patterns in asset returns.

$$\textit{Capital Asset Pricing Model,} \quad E(R_i) = R_f + \beta\left(ER_m - R_f\right) \tag{2}$$

Where $E(R_i)$ is expected return on investment, R_f is the risk-free rate (usually as estimate for R_f one month U.S. T-bill rate is used), ER_m is expected return on market and β is beta coefficient of asset.

Although of its publicity and popularity, CAPM is a very simple definition of how assets are priced and how the risk should affect directly to the expected return of the stock. Because of this simplicity, CAPM suffers many drawdowns when compared to what we have seen in equity markets and empirical studies. More sophisticated models take many different characteristics into account that affect or may have an effect on explaining expected returns. Those explanatory variables are, for example, the risk factors such as value, quality, and profitability that were discussed in chapter three.

Performance of time-series asset pricing models is usually evaluated by different statistical measures. It is also relevant how steady those statistical measures are with different datasets over the markets and countries. Moreover, is the model able to explain returns universally or just from the particular equity market? Most well-known and easy to intercept performance measures are the regression intercept also referred as alpha of regression, adjusted R^2 -value and when making multiple regressions the CRS test static value by Gibbons, Ross, and Shanken (1989). Asset pricing models try to achieve as low as possible insignificant intercept. When evaluating asset pricing models in empirical tests, intercept means that there is some variation that regressors (risk factors, for example) are not able to explain. There is something that affects asset prices, but the model is not able to explain that variation. Thus, if exposures to different factors capture all variation in the expected returns and intercepts are zero for all stocks and portfolios to be tested, the conclusion can be made that these values are true values of the population rather than just estimates (Fama & French, 2015).

R^2 adjusted is the measure of regression fit, and it defines how well regressors can explain the returns. It punishes by lowering the value if there are unimportant regressors that really are not explaining returns. Easy to understand, higher the adjusted R^2 value, higher the explanation power of the asset pricing model. CRS-value tests all the regression intercepts in the joint examination, as there is the possibility that single intercept value is not significant, but in the joint examination, intercepts are significant (Gibbons et al. 1989). Intercept, R^2, and CRS-values are statistics that are mainly used to evaluate the performance of asset pricing models in this study. Getting high R^2, low insignificant intercept and not getting rejected by CRS test does not face easy job, but as Fama and French (2015) state “asset pricing models are simplified propositions about expected returns that are rejected in tests with power” (p. 10). Based on this statement and the difficulty of finding all the possible explanatory for returns, asset pricing models are more of finding the best possible alternative to explain returns (Fama & French, 2015).

4.1 Fama-French Three-factor Model

Fama and French (1993) studied common factors in returns of stocks and bonds, which resulted in the creation of a three-factor asset pricing model (later FF3). Fama and French found that size measured as market capitalization, BE/ME book-value to market-value of equity and market return minus the risk-free rate had high explanation power of the U.S. stock returns. Fama and French used time-series regression approach to point out the importance of these risk factors in empirical tests. In the time-series regression approach, monthly excess returns on stock portfolios sorted by different characteristics are regressed against portfolios created to mimic factor returns. Risk factor portfolios used in their study were market factor (later MKT, that means market portfolio returns minus the risk free rate), size factor (later SMB, that means small-minus big, difference in simple returns between three small and three big portfolios that have similar BE/ME) and value factor (later HML, that is similar to SMB, but build on difference in simple returns between two low and two high BE/ME portfolios). To form factors and stock return portfolios, value-weighted returns were used. This was because value-weighted returns reflect more realistic investment opportunities in the market than the equally-weighted approach. (Fama & French, 1993)

4.1.1 Performance and applications

Outcomes from regression referred to as coefficients or slopes of regression then show the loadings and sensitivities of excess returns on these three risk factors MTK, SMB and HML. This approach is convenient because slopes and R^2 values show how well factor portfolios can imitate returns on factors and to capture variation in stock returns. FF3 regressions made to explain returns were successful as regression intercepts were close to zero and R^2 values high. These findings on empirical tests confirm that factors made from the market return, size, and BE/ME can explain differences in returns, and there are at least three factors in the equity market. This study resulted in the creation of well-known asset pricing model referred to as the three-factor model that was able to explain returns in 1963 – 1990 period better than previous asset pricing models. FF3 model was extending the CAPM by Sharpe and Lintner as it suffered multiple drawdowns with empirical data and lack of explanation power compared to FF3. (Fama & French, 1993)

$$FF3, \qquad R_i - R_f = a + b_i MKT + s_i SMB + \ h_i HML + \in_i \tag{3}$$

Where $R_i - R_f$ is the excess return on portfolio to be explained, a is the regression intercept, MKT market portfolio excess return, SMB size factor portfolio returns, and HML value factor portfolio returns, b_i, s_i, h_i are regression parameters, and $\in_i$ is error term.

FF3 allows for many applications in empirical studies, for example, to study sources of abnormal returns on event studies or to evaluate the performance of active portfolio management more accurate than using an alternative model such as CAPM. (Fama & French, 1993) In performance tests, Fama and French (1996) show that the three-factor model is successful in explaining return differences in anomalies such as sales growth, earnings-per-price and cashflow-per-price discovered in the equity markets and seen as anomalies by CAPM. Those anomalies disappear and are explained by different loadings on SMB and HML risk factors. This simply means that these firms have different characteristics and differences in returns are explained by differences in size and BE/ME ratio. Sales, E/P and C/P can be viewed as subcomponents to these factors as their return premiums are captured by size and BE/ME factors, thus subcomponents providing no further information. However, it was discovered that the three-factor model was unable to explain the momentum effect discovered by Jegadeesh and Titman (1993) in the empirical part of this study. (Fama & French, 1996)

Griffin (2002) studied whether the factors in FF3 are country-specific or international by comparing country-specific FF3 to global FF3. Griffin studied whether the SMB and HML factors made from international stock market returns or from domestic stock market returns can better explain on a country-specific basis. Results of the study show that the domestic model is easily beating the world factor model in this task. Domestic models were able to explain much more time-series variation and had less pricing errors than world factor model did. Adding foreign factors to model was not able to improve the explanatory power of the model on stock and portfolio returns. Based on these findings, extending the model to the international context is not useful. Griffin concludes that for practical applications of FF3, the model should be built with country-specific return data and usage of the wrong model could lead to wrong conclusions as there is a large variation between performance of these alternatives on explaining country-specific returns. (Griffin, 2002)

4.1.2 Critical view on three-factor model

After the publication, FF3 has been tested, criticized, studied, and modified on several cases which shows its importance to asset pricing literature. Critics to FF3 has been made by Kothari, Shanken, and Sloan (1995). They argue that results found in Fama and French (1993) were largely due to survivorship bias in the COMPUSTAT database and biased research set up to study explanation power of factors. Comparing different databases with the COMPUSTAT database lowers the difference of BE/ME on returns by a significant 40 %. For example, returns of small firms in the COMPUSTAT database are 9 – 10 % percentage points higher than CRSP – COMPUSTAT returns. Kothari et al. use also the S&P industry-level data to show that data in the COMPUSTAT database may be influenced by survivorship bias on firms that were used to study BE/ME return association. Also, making industry portfolios from COMPUSTAT data lower the return association, which suggest that the research setup is determining the results. Another argument to biases research setup, was against beta risk, that Fama and French (1993) does not consider substantial in determining asset returns. Using annual instead of monthly beta estimates shows the compensation for beta risk more precise than using the monthly values. There is also concern on data-snooping as returns on different BE/ME has been varying around time, which may have affected the results based on data period selection. (Kothari et al. 1995) This critic of biased data selection period and time-varying effect of BE/ME returns is much brought down by tests of Fama and French (2015) as they can show that patterns are similar to that made in Fama and French (1993) with 21 years of new data.

Petkova (2006) argues that FF3 factors are related to time-varying investment opportunities. This explanation is supported by Vassalou (2003), who shows that information content and explanatory power of SMB and HML reduces as macroeconomic risk is taken into account. The asset pricing model that is built by choosing only the variables that have forecasting power to future investment opportunities such as different state variables (e.g. aggregate yield, term spread, default spread, one-month T-bill etc.) can explain returns better than FF3. Petkova argues that SMB and HML are only proxies for state variables that can predict future excess returns and the yield curve. This means that SMB and HML are highly correlated to different state variables. This is supported by the fact that FF3 factors lose their explanatory power as state variables are added to the regressions. (Petkova, 2006) Fama and French (2015) answer to this critique in the way that variables in their asset pricing models are not state variable imitating portfolios, moreover these portfolios are presenting and providing different combinations of exposures and links to unknown state variables. This easies the job capturing this variation with a couple of factors without necessarily identifying the all unknown state variables. (Fama and French, 2015)

4.2 Fama-French Five-factor Model

To partly to answer the critics against the FF3 and improve performance of their model to the present day, Fama and French (2015) developed the five-factor model (later FF5) that adds two factors to the original FF3. Those factors are profitability and investments factors, that can be seen as quality characteristics of a firm. As discussed in chapter three, Noxy-Marx (2013) points out the importance of quality characteristics of a firm in expected returns. Profitability and investment factors were chosen because they seem like natural choices based on the decomposition of the dividend discount model. Decomposition suggests that expected return on the stock is determined by the price-to-book ratio, expected future investments and profitability. There are also variables such as size in the model that are not directly linked to the decomposition of this model but may help in improving forecasts of future investments and profitability capturing the horizon effect of expected returns. Empirical evidence also supports these factors as Fama and French (1993) states that FF3 leaves much of variation in excess returns unexplained by related differences in profitability and investments of firms. Definitions of new factors are robust-minus-weak, RMW, which is profitability factor that is built as the difference between diversified portfolios of stocks with robust and weak profitability. Conservative-minus-aggressive, CMA which is investment factor which is built as a difference in returns between diversified portfolios of stocks that have high or low investments. (Fama & French, 2015)

$$FF5, \quad R_{it} - R_{Ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \in_{it} \quad (4)$$

Where $R_{it} - R_{ft}$ is the excess return on portfolio to be explained subject to time, a is the regression intercept, MKT market portfolio return minus the risk-free rate, SMB size factor portfolio returns, and HML is value factor portfolio returns, RMW is the profitability factor, CMA is the investment factor, b_i, s_i, h_i r_i c_i are regression parameters, and $\in_{it}$ is error term.

4.2.1 Performance and applications of five-factor model

Fama and French (2015) five-factor model is successful in explaining variation in excess returns in multiple categories that are created in similar, but adjusted way to FF3 by creating portfolios based on size, investments, profitability and BE/ME. Those portfolios are finer sorts from variables that are used to build FF5 factors. On empirical tests, only a couple of extreme sorts pose difficulties to the explanatory power of FF5. These sorts are in small stocks that invest a lot despite having low profitability.

BE/ME portfolio sorts show that average returns increase with BE/ME in every size row. The difference is nearly one percentage with the smallest size category per month when comparing the lowest BE/ME sort to highest BE/ME sort. In biggest size category, this value effect between lowest and highest sort reduces to 0.16 % difference per month. The value effect discovered in empirical studies is highly visible in those portfolio sorts (Fama & French, 2006; Asness et al, 2013). Similar results can be found when investment portfolio sorts are made. In every size quantile, the lowest investment category has significantly higher average returns, and those returns increase in portfolios at smaller size categories. This result was in line what was expected due to empirically discovered low asset growths association with lower returns (Fama & French, 2006; Cooper et al. 2008; Watabane et al. 2013). However, using three-way categorization, the valuation equation does not predict the fact that the effect of investments, operating profitability and BE/ME do not show in average returns without proper controlling of factors. This fact calls for the need to sort them differently to point out differences in average returns. Thus, variables are sorted differently, creating thirty-two portfolios in each category which allows controlling for one variable. Portfolios are categorized by three variables, for example, sort on size, BE/ME and operating profitability. This reveals patterns in excess returns as anticipated. Small stocks have strong value, profitability, and investment effects in their average returns based on those sorts. Patterns are also similar in big stocks category but showing a weaker pattern in returns. (Fama & French, 2015)

Evaluating the performance of FF5 model is evaluated against FF3 and different four-factor models combining these factors. Performance tests are made with several summary statics, for example, absolute alpha and CRS value. CRS test rejects all models considered, which suggest that models are incomplete descriptions of returns. But as brought out earlier by Fama and French (2015) statement, it is about finding the best alternative. For comparison, FF5 produces lower CRS test statics and absolute alphas with lower dispersion than FF3. Biggest improvements are in new sorts of thirty-two portfolios, which is anticipated as FF3 is not targeting CMA and RMW risk factor effects on average returns. What was interesting in those results was that FF5 has similar statics to the four-factor model that excludes the HML factor. This fact calls for a revaluation of HML factor in the FF5 as it seems that value factor returns are captured by other factors and HML is really redundant at least in 1963 – 2013 U.S stock sample. This is also confirmed by regressions between factors showing the insignificance of the HML factor. Quality paper by Novy-Marx (2013) did little bit anticipate this with its results showing value-based strategies association with quality strategies. Anyhow, testing differences between adjusted HML factor, four-factor and FF5 show only marginal effects on regression coefficients and similar explanation power between the alternative models. Thus, pattern and explanations remain the same no matter what model of these alternatives are used. Despite poor performance on CRS tests, FF5 can explain almost all variation in these test portfolios formed by different characteristics. Almost all unexplained returns are close to zero, and the model can explain 71 – 94 % of the cross-sectional variance of sorted portfolios examined in the study. The only exception to this was small firms that invest a lot despite low profitability, which returns FF5 does not capture. (Fama & French, 2015)

4.2.2 Dissecting anomalies and international tests

Testing the performance of FF5 on explaining anomaly patterns in returns was done similar to tests made with FF3 on anomaly return patterns. Fama and French (2016) test FF5 power to explain returns associated with returns anomalies such as accruals, net share issues, momentum and volatility. FF5 was able to explain and shrink the list of anomalies as they show similar exposures to FF5 factors suggesting they are related to the same phenomena in general. Anomalous patterns in low beta stocks, low volatility, and share repurchases are explained by the exposures to CMA and RMW risk factors. The expectation to this were accruals and momentum anomalies that pose problems earlier on to the FF3 too. In accruals patterns, extreme quantiles pose problems to FF5, and it does worse in explaining returns than FF3. Momentum is also a problem for FF5, and this could be anticipated because portfolio sorts do not provide momentum effects that the model is trying to explain. Adding momentum factor to FF5 model provides better explanation power, but still leaving some of the extreme small sorts unexplained. Adding momentum factor is also kind of playing the home game by creating a portfolio with the same returns as the factor itself. FF5 is adding to the explanation of common returns by shrinking down the list of anomalous return patterns significantly. Most of the problems posed to the model are concentrated on the extreme portfolio sorts such as microcaps, which we know play a very minor part in equity markets. (Fama and French, 2016)

Testing out of sample performance of FF5, Fama and French (2017) conduct international tests on North America, Europe, Japan, and Asia Pacific equity markets. They use approach to build factors from domestic data rather than trying to build a global asset pricing model in line with the findings of Griffin (2002) on FF3. Based on this Griffin and Fama and French (2017) findings from international markets, it seems impossible to build a universal model that can explain country-specific returns with factors that are created globally. This holds at least for FF5 and similar models.

Accurate estimates to factor sensitivities call for the need of creating portfolio sorts and factors from the same domestic return data.

Findings follow mainly the same results found in Fama and French (2015, 2016). Average returns increase with book-to-market and operating profitability. Patterns found in portfolio sorts are weaker for big stocks. Local versions of FF5 can explain most value, profitability and investment patterns in average returns. Small stocks seem to pose some problems to FF5, but some patterns in small stocks were explained well by FF5. Most interesting findings on international tests were that CMA seems to be a redundant factor in explaining returns in Europe and Japan. Portfolio sorts show that small firms that invest a lot despite being unprofitable seem to have extreme -0.65 % and -0.71 % per month negative excess returns in Europe and the Asia Pacific, and low but less extreme positive excess return of 0.12 % in North America. Returns are substantially lower for the highest investment portfolios, but the pattern is less prominent in big stocks in line with other tests. In Japan, only BE/ME and average returns seem to have high relation with each other, which is explained well by coefficient loadings to FF3. (Fama & French, 2017)

4.2.3 Critical view on Fama-French five-factor model

Adding two factors to the three-factor model seems like a long leap from FF3 to the creation of FF5 model as HML is redundant in some tests, CMA does not play an important part in explaining returns universally, and four factors can do the job same way as FF5. Blitz, Hanauer, Vidojevic and van Vliet (2016) find possible problems that should be considered based on the FF5. Main concerns focus on the factor selection of the FF5 as Fama and French (2015) choose two new factors that could be identified as quality factors. Although these are only two quality characteristics of the firm, so it is a fair argument why to choose only two of those opposed to the fact that Novy-Marx (2013a) and Asness et al. (2019) discover several quality characteristics of the firm that could be used in factor selection. Building the FF3, the main focus was on the risk-based explanations that build strong foundations to the model. However, in FF5, the economic rationale between the selected factors lies much weaker explained and less clear than before. The FF5 also maintains its CAPM relation with the market beta and the expected returns opposed to the fact that it has been shown empirically that this relation is flatter or even negative with empirical data. On another way around Blitz et al. are surprised why momentum is not included in some way to the FF5, although momentum has been studied widely and there have been found long-lasting robustness behind its risk premium and return patterns. These problems with the model may eventually lead to the outcome that not much debates can be settled or consensus understanding to be drawn based on the FF5. These concerns question the importance of FF5 to asset pricing literature. (Blitz et al. 2016)

4.3 Conclusions on Fama-French Models

Findings of Fama and French (2017) CMA as being redundant factor and patterns being mostly invisible in returns of Japan were very interesting on the view of this study. Japan has long lived in a period of low-interest rates and low gross domestic product growth (later GDP). GDP growth has been around 1 % annual in the period of 2010 to 2017 following the sharp drop of 5.5 % in 2009 after the financial crisis. Similar figures in Europe was 1.5 % and a drop of 4.5 %. In the U.S. GDP growth has been around 2 % and the drop was only 2.5 %. GDP growth rates have been collected from Google public data that is created based on data of The World Bank (2017). Japan and Europe lack CMA factor as it is redundant, and in Japan patterns in returns are not visible the way they are in the U.S. in the test period data of 1990 – 2015 that was used in Fama and French (2017). These results may give some direction what results of this thesis may show as interest rates and growth rates have been low in Europe and in the U.S. after the financial crisis. Anyhow, interest rates and growth are not as low as in Japan and period has been short compared to what Japan has suffered, but these low rates could be a sign of lower importance of CMA factor and weaker patterns in the U.S. returns in the 120 months of 01/2009 to 12/2018.

Finding of Griffin (2002) and Fama and French (2017) show that FF models are not able to explain returns with universal factors, so it is not pleasant to try to build a universal model similar to FF3 and FF5 models. This evidence shows that this is not possible due to the lack of explanatory power in universal factors to differences between countries. Countries pose such differences that a model containing five factors seems to be too large on some occasions. Could there be some more universal factors or state variables that can explain returns on a more universal basis? There are also critics like Blitz et al. (2016) on factor selection of the FF5. Models and portfolio sorts, however, provide us with much new information on existing patterns on common stock returns and the way that markets are pricing different assets with different exposures to risks. Applications of FF3 and FF5 models also widen the field to make event studies and understand sources of returns by different portfolios, indexes or funds. Models and findings of Fama and French (1993, 1996, 2015, 2016, 2017) provide much new insight on asset pricing literature.

In conclusions of paper Fama and French (2017) state that time variation in the slopes could pose potential problems to FF3 and FF5 models. They, however, point out that it would be not too serious if we want to evaluate, for example, the performance of the actively managed fund. Intercept will capture the variation that is left unexplained by the factors. (Fama and French, 2017) Studying the magnitude of this variation on regression coefficients is exactly what this thesis is going to study in the next chapter. Statement of Fama and French (2017), evidence of risk factors related to macro-economic state variables (Petkova, 2006), Cochranes (2017) deduction on market states and stock prices among other empirical evidence strongly supports the first hypothesis of this study: there are significant changes in risk-factors after the financial crisis. This hypothesis anticipates strong changes in priced risks between two periods before and after the financial crisis using the end of 2008 as a breakpoint for data.

We are also interested in how much the regression intercepts and R^2 values change because of changes in the market caused by the financial crisis. This should tell us how much performance of FF5 is affected by the changes in market states. Changes in performance can be anticipated based on the same findings of previous studies. This supports the creation of the second hypothesis: the performance of FF5 is affected by different states in the market. To find more prominent evidence to support these hypotheses among other hypotheses, this thesis next tests the FF5 on three different periods with differently shorted stock portfolios.

5 FIVE-FACTOR MODEL IN DIFFERENT MARKET STATES

Aim of this thesis is to study significant changes in major risk-factors between the 120 months before and after the financial crisis using the end of 2008 as a breakpoint. Research set up follows a mainly similar approach as Fama and French (1993, 1996, 2015, 2016, 2017) studies by using portfolio sorts of different characteristics and portfolios that mimic risk factor returns. This thesis adds to the existing literature by evaluating three short periods with high-frequency data of 120-months (2515 – 2528 daily obs.) and comparing relative changes on these periods. This is kind of a different approach than used in the existing literature. This thesis takes a view on asset pricing on an event-based study set up focusing on the financial crisis.

First, the main focus of this chapter is comparing risk factor pricing patterns and performance of FF5 in (01/1999 – 12/2008) period to (01/2009 – 12/2018) period in the U.S. equity market (using returns from 3424 – 5201 firms on average during different periods). These two periods can be seen as the period before the financial crisis and period after the financial crisis. Period one (control period) is added to the analysis to study and point out the magnitude of changes in the latter two periods. Second, this chapter studies the regression coefficients from 321 regression tests which reveal the changes in risk factor coefficients and risk factors importance on explaining common returns. This should shed some light to following four questions and help to answer the research questions of this thesis. (1) how the different states on the market affect risk factors (2) does the risk factor pricing patterns found in the previous empirical studies hold in shorter periods with high frequently data (3) what is the magnitude of the effect of global financial crisis on the risk factors and (4) how steady is the performance of FF5 model between different market states.

5.1 Research Method

Previous empirical studies have been able to identify the most important risk factors that were discussed in chapters three and four. Based on the empirical evidence provided in those chapters, the Fama-French five-factor model is used to study changes in the U.S. equity market before and after the financial crisis in this thesis. FF5 can be identified as the best alternative to explain and capture variation, as it has been shown that FF5 performance is high with U.S. return data. These previous findings suggest that FF5 is the best model to answer questions assessed by this thesis. Research method follows studying the return patterns of differently sorted portfolios that should show the effects of risk factors and conducting multiple regressions tests to study changes in regression coefficients and model performance.

FF5 is used in multivariate time-series regression approach, which means that the left-hand-side (later LHS) variable is the excess return on the portfolio created by different characteristics. Right-hand-side (later RHS) variables are the returns on different portfolios that are created to mimic risk factor returns similar to Fama and French. Time-series regression coefficients then give different risk factor loadings in LHS portfolio excess return as the outcome. Regression statistical measures tell about the explanatory power of the FF5 model. These outcomes from regression tests allow this thesis to conduct analysis which answers the research questions assessed by this thesis by comparing differences in coefficients and statistics between those periods.

5.1.1 Data

Data is collected from Kenneth R. French (2019) data library which provides similar and updated data as used in Fama and French (1993, 1996, 2015, 2016, 2017) studies. Return data in Kenneth. R French database is collected from CRSP and COMPUSTAT databases, and there have been added firms that are hand-collected from the Moodys Industrial, Transportation, Utilities, and Financial Manuals. Return data includes all stocks from AMEX, NYSE, and NASDAQ which had market equity data for December of (t)-1 and June of (t), and positive book equity data for (t)-1 (requirement for book-to-market, operating profitability, investments, and factor portfolios), non-missing revenues data for (t)-1 and data at least one of following variables: cost of goods sold, selling, general and administrative expenses, or interest expense for (t)-1 (operating profitability, factor portfolios) and total assets data for (t)-2 and (t)-1 (investments, factor portfolios). R_m uses value-weighted returns of all CRSP firms that are incorporated in the U.S., listed in NYSE, AMEX, or NASDAQ having CRSP code 10 or 11 at beginning of the month of (t), and good return data for (t). One-month U.S. T-bill rate is used as a proxy for the risk-free rate. (Kenneth R. French Database, 2019)

Data selected includes daily and monthly value-weighted average returns on 2x3 portfolio sorts (6 portfolios), formed to mimic FF5 factor returns. Daily value-weighted average returns on 5x5 portfolio sorts (25 portfolios) formed on size and book-to-market, size and operating profitability and size and investments. Monthly value-weighted average returns on 2x4x4 sorts (32 portfolios) on formed on size, operating profitability, and investments. Data is collected for both sorts on three 120-month periods: (01/1989 – 12/1998), (01/1999 – 12/2008), and (01/2009 – 12/2018). These different portfolio sorts are LHS variables in the regression tests. Daily and monthly value-weighted average returns for risk factor portfolios and the risk-free rate are collected for the same periods. These risk factor portfolios are RHS variables in the regression tests. Data includes 2528 daily and 120 monthly return observations in (01/1989 – 12/1998) control period/period one. 2515 daily and 120 monthly return observations in (01/1999 – 12/2008) period two. 2516 daily and 120 monthly return observations in (01/2009 – 12/2018) period three. The average number of firms has a large decrease coming to period three. However, this decrease is significant only on the smallest firm size category, and other size quantiles are pretty steady over periods. Changes in the number of firms can thus be seen as a normal outcome of recession and not biasing results found on this thesis. Detailed tables of the average number of firms in each of the portfolios you can find from the appendix one.

This thesis uses daily data on 5x5 portfolios sorts to get more accurate estimates of risk factor loadings and movements. The main focus of this thesis is on these 5x5 portfolio sorts. On three-variate sorts, only monthly return data is provided and used. Thus, three-variate sorts provide only supplementary information to study these research questions. Using daily data on 5x5 sorts is different from Fama and French studies as they used a monthly approach in all portfolio sorts. Value weighted average returns are used in all tests as value-weighted returns give a more realistic view on real-world investment opportunities than equally-weighted data (Fama & French, 1993). Usage of Kenneth. R. French database is supported because it provides unique return data created with an approach that combines multiple databases confirming that data in this thesis is a robust variable. Publicly available data allows repeatability of this thesis and the possibility to study and compare different periods similar to this thesis.

5.1.2 Variable construction

This subchapter follows closely on what is provided about variable construction on Kenneth R. French Database to give the reader clear thought how returns are formed. Risk factor mimicking portfolios are built the following way. SMB, small-minus-big (size factor) is built as the difference in average returns on the nine small stock portfolios minus the average return on the nine big stock portfolios. Three small and big portfolios are built on each category (book-to-market, operating profitability, investments), resulting in a total of nine small and big portfolios. SMB is an estimate that shows the difference in average returns between small and big firms. HML, high-minus-low (value factor) is built as the difference in the average returns on the two value (high BE/ME) portfolios minus the average return on the two growth (low BE/ME) portfolios. HML is an estimate of return difference between value and growth firms. RMW, robust-minus-weak (profitability factor) is built as a difference in average returns between two robust operating profitability portfolios minus two weak operating profitability portfolios. RMW is an estimate of return difference between firms that have robust operating profitability and the firms that have weak operating profitability. CMA, conservative-minus-aggressive (investment factor) is built with a difference between two the conservative investment portfolios minus two aggressive investment portfolios. CMA is an estimate of return difference between low total asset growth firms and high total asset growth firms. The more detailed description and formulas behind factor construction are provided in Kenneth R. French Database and Fama and French (2015) study. (Kenneth. R. French Database, 2019)

Portfolio average returns are more accurate sorts of the same return data as used in the risk factor construction. First, 5x5 sorted portfolios. All portfolio sorts are constructed at the end of June. Size and book-to-market portfolios are constructed as intersections of five portfolios formed on size (market equity) and five portfolios formed on book-to-market. Size breakpoints for the year (t) are the NYSE market equity quantiles at the end of June (t). BE/ME for June in the year (t) is the book equity for the last fiscal year-end in (t)-1 divided by ME for December of (t)-1. Breakpoints for BE/ME are NYSE quantiles. Similar ten portfolio intersection is created to size and operating profitability. Five of each portfolio are created for size and operating profitability. Operating profitability for June of the year (t) is annual revenues minus the cost of goods sold, interest expense, selling, general and administrative expenses divided by book equity for the last fiscal year-end in (t)-1. Resulting in a profitability ratio. Breakpoints for size and operating profitability again as NYSE quantiles. Similar five portfolios are created for each sort in size and investment. The intersection of these portfolios creates 25 portfolios. Investments are the change in total assets from the fiscal year ending in the year (t)-2 to the fiscal year ending in (t)-1, divided by (t)-2 total assets. Resulting in a total asset growth percentage. Breakpoints for portfolios are used again as NYSE quantiles for size and investments. Three-variate sorts (2x4x4) portfolios are allocated in two size groups using NYSE median market cap as the breakpoint between small and big firms. In each size group, stocks are allocated in four groups based on operating profitability in (t)-1 and investments similar as in 5x5 sorts. Using again NYSE breakpoints specific to each category to define breakpoints for portfolios. Descriptions of variables (size, operating profitability, investments) in 2x4x4 sorts are same as in 5x5 portfolio sorts. (Kenneth. R. French Database, 2019)

5.1.3 Average returns on Fama-French factors

Average daily returns for Fama-French five factors are reported below in table one. The interesting difference among the tables can be seen from table 1.b. It shows that average and median returns on all factors have been relatively high and all positive in the period two of (01/1999 to 12/2008) expect for the market minus risk-free average. Risk-factors excluding the market excess return has not been driving positive returns on the period three on average or with the median values. Averages and medians are close to zero in control (table 1.a) and on period three (table 1.c). This is good news as returns should be around zero as the five factors are made to differentiate firms based on these characteristics.

Among the other differences in risk factor average returns around the periods, the most important difference that can be seen from these tables is the low risk-free rate in the in period three (table 1.c). It shows that the risk-free rate has been on average, 0.001 percent daily. This is only 0.252 % on an annual basis if we use 251.8 trading days on average a year on this period. Period three is characterised with low costs to use borrowed money, and this should have some effects on markets and risk-factors.

Table 1.a Average daily returns on Fama-French five factors and the risk-free rate on time period of (01/1989 – 12/1998)

	$M_R - R_f$	SMB	HML	RMW	CMA	R_f
Average	0,049	-0,018	0,009	0,019	0,007	0,020
Stand. Dev.	0,797	0,479	0,393	0,249	0,351	0,006
Median	0,070	0,000	0,000	0,010	0,000	0,020

Table 1.b Average daily returns on Fama-French five factors and the risk-free rate on time period of (01/1999 – 12/2008)

	$M_R - R_f$	SMB	HML	RMW	CMA	R_f
Average	-0,006	0,025	0,023	0,027	0,023	0,013
Stand. Dev.	1,341	0,655	0,707	0,639	0,535	0,007
Median	0,040	0,050	0,010	0,010	0,010	0,013

Table 1.c Average daily returns on Fama-French five factors and the risk-free rate on time period of (01/2009 – 12/2018)

	$M_R - R_f$	SMB	HML	RMW	CMA	R_f
Average	0,054	0,003	-0,007	0,004	0,001	0,001
Stand. Dev.	1,071	0,544	0,620	0,355	0,305	0,002
Median	0,070	0,000	-0,030	0,000	-0,010	0,000

Table one presents average daily returns, median daily returns, and standard deviation of return for Fama-French risk-factors and the risk-free rate for three time periods evaluated in this thesis. For a detailed description of factors check chapter 5.1.2 Variable construction.

5.2 Tests on Size and Book-to-Market Portfolios

The first part of the analysis focus on the risk factor patterns on average returns on the portfolio sorts of size and book-to-market on three different periods. Hoping that average returns provide clear patterns in returns that follow the risk factor effects that have been identified by the previous studies. Second, the performance of the FF5 model is evaluated and compared with regression intercepts and adjusted R^2 values and R^2 dispersion. CRS tests are not conducted and reported, as they are most likely to dismiss the model as seen in Fama and French (2015) providing no further information to analysis and comparison. The third part of this subchapter, regression coefficients interpreted as risk-factor loadings and their relative changes during the three periods are evaluated, compared, and analysed. At the end of this subchapter, there is a short chapter that concludes the highlights found on different tests.

In the evaluation of risk factor coefficients, absolute average values are used when discussing all coefficients jointly to effectively squeeze up main changes between the periods from a large number of coefficients. Main changes on single coefficients are also brought up if those are visible and significant additions to the analysis. Using absolute values on averages when there are highly positive and negative values gives the real value on which the factor has on explaining the returns on either direction as all factors excluding the market excess return provides positive and negative coefficient values. Thus, using only average values provide not the real importance of risk factor. To effectively understand the coefficient comparison, for example, the coefficient value of 0.5 means that as the return for risk factor increases 1 % the return of these firms having this coefficient increase by 0.5 % on average. If the coefficient is negative -0.5 the returns decrease by -0.5% as factor return increase 1 % and opposite. Absolute values then give the importance of explanatory power of the risk factor if values differentiate highly from negative to positive. In calculating the absolute averages, all coefficients are used in comparison if most of the coefficients are significant (twenty or more) and those are reported in each comparison. Insignificant coefficients are most likely close to other coefficients not changing the main story behind the average of coefficients. This approach gives the reliable direction of the trend but could not be viewed as the absolute change on coefficients. Significant single coefficients give a more realistic view of absolute change.

5.2.1 Return patterns

Average returns for twenty-five different portfolios sorted on size and book-to-market are reported below in table two. The patterns in control period (table 2.a) follow closely BE/ME effect as high book-to-market stocks have higher returns in the first three size columns. In the fourth size column, the effect is similar but not as strong. In biggest size column value effect seems to mix for a bit having the highest return in the table at the lowest row of BE/ME and almost as high return in the highest row of BE/ME. Average returns table for the period one shows that BE/ME effect is stronger in small stocks, but the highest returns are still achieved in biggest size columns.

Returns are very close to each other when comparing differences in average returns between the size columns. Only the smallest and biggest size column at the lowest BE/ME row, and biggest size column at the highest BE/ME row excludes from this similarity in average returns. Average returns from the first period (table 2.a) show no support to size effect in this period and sort. Size effect seems to be reversed as bigger size columns have higher returns than small size columns.

Table 2.a Period one: Average daily returns on (SIZE&BM) 01/1989 - 12/1998

	Small Size	2	3	4	Big Size
Low B/M	0,010	0,041	0,055	0,061	0,085
2	0,047	0,047	0,056	0,059	0,068
3	0,049	0,056	0,059	0,057	0,069
4	0,062	0,066	0,062	0,066	0,064
High B/M	0,063	0,063	0,066	0,066	0,083

Table 2.b Period two: Average daily returns on (SIZE&BM) 01/1999 - 12/2008

	Small Size	2	3	4	Big Size
Low B/M	-0,004	0,007	0,004	0,026	-0,002
2	0,037	0,034	0,035	0,029	0,020
3	0,037	0,044	0,033	0,022	0,020
4	0,058	0,041	0,033	0,037	-0,004
High B/M	0,049	0,037	0,059	0,018	0,013

Table 2.c Period three: Average daily returns on (SIZE&BM) 01/2009 - 12/2018

	Small Size	2	3	4	Big Size
Low B/M	0,043	0,069	0,063	0,069	0,060
2	0,056	0,068	0,064	0,065	0,054
3	0,053	0,060	0,055	0,058	0,055
4	0,054	0,048	0,061	0,056	0,044
High B/M	0,057	0,054	0,050	0,060	0,052

Table two presents average daily returns for 25 portfolios sorted by size measured as market capitalization and the book-to-market ratio for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis).

Patterns in period two (table 2.b) also show support to BE/ME effect in average returns. The only expectation is the biggest size column which has average daily returns of (0.009 %) and returns are mixed through BE/ME rows. Returns increase as BE/ME increases strictly following BE/ME effect in first four size columns, excluding the highest BE/ME row which has a bit lower returns than other BE/ME rows. Third size column of medium-sized firms that have high BE/ME ratio has the highest average returns on period two (table 2.b). The size effect is well visible in this second period as smaller size columns have almost systematically higher average returns than bigger size columns.

Patterns in period three (table 2.c) show that the BE/ME effect seems to reverse in this period. Only smallest size column shows persistence in BE/ME effect. On other size columns, returns increase as BE/ME ratio lowers and highest returns in (table 2.c) are found in the lowest BE/ME row in the biggest four size columns. The size effect is also invisible in this period, as no clear patterns in returns could be seen. These results from the last table need to be viewed with the fact that all returns are very close to each other as the range is between (0.043 - 0.069). Differences between the (01/1999 - 12/2008, table 2.b) and (01/2009 - 12/2018, table 2.c) seem significant. BE/ME and size effect lose its differentiation power in the third period, and returns are much closer to each other. Dispersion in returns on period two is (-0.004 to 0.059) and on period three (0.043 to 0.069). In the control period, this is (0.010 to 0.085), which is more similar to the second period the same way as BE/ME patterns are more visible in the periods one and two. Exceptional in period three (table 2.c) is a fact as there are not even close to zero returns on each of the sorts. Firms in all categories have been providing steady and similar average returns with no matter the differences in characteristics.

5.2.2 Performance of FF5

Table 3.a Period one: Adjusted R^2 values for regression (SIZE&BM) 01/1989 - 12/1998

	Small Size	2	3	4	Big Size
Low B/M	0,886	0,939	0,920	0,888	0,957
2	0,861	0,906	0,885	0,875	0,910
3	0,833	0,884	0,858	0,867	0,883
4	0,821	0,866	0,849	0,844	0,894
High B/M	0,859	0,847	0,809	0,763	0,804

Table 3.b Period two: Adjusted R^2 values for regression (SIZE&BM) 01/1999 - 12/2008

	Small Size	2	3	4	Big Size
Low B/M	0,885	0,956	0,941	0,926	0,979
2	0,905	0,950	0,931	0,902	0,915
3	0,923	0,945	0,910	0,872	0,882
4	0,924	0,949	0,900	0,880	0,892
High B/M	0,926	0,941	0,884	0,842	0,849

Table 3.c Period three: Adjusted R^2 values for regression (SIZE&BM) 01/2009 - 12/2018

	Small Size	2	3	4	Big Size
Low B/M	0,921	0,961	0,951	0,942	0,976
2	0,940	0,968	0,960	0,944	0,962
3	0,954	0,975	0,955	0,937	0,948
4	0,953	0,974	0,952	0,936	0,943
High B/M	0,963	0,966	0,933	0,936	0,927

Table three presents the adjusted R^2 values of the 25 regressions made to portfolios sorted on size and book-to-market for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis). For a detailed description of the adjusted R^2 value check the first part of chapter 4. Asset pricing models.

Performance measured as adjusted R^2 values and intercept values is the weakest in the control period (table 3.a). R^2 dispersion is high (0.193) between the lowest and highest value, average absolute intercept is (0.007), and in twenty-five regressions, there were seven significant intercept values by using 95 % confidence level t-test. These significant intercept values were mostly in the smallest (3), and the biggest (2) size columns. Performance increased in terms of R^2 values and number of significant intercepts on period two (table 3.b). R^2 dispersion is (0.137) between the lowest and highest value, absolute intercept is (0.009), and in twenty-five regressions, there were five significant intercepts on a 95 % confidence level t-test. Results from the second period are very close to the control period as FF5 only slightly improves test statics from the control period. In period three (table 3.c), significant improvement is seen as FF5 was most successful in explaining average excess returns. R^2 dispersion as low as (0.055) showing steady performance between portfolios, the absolute intercept was low as (0.004) with zero significant values. Even the lowest R^2 was (0.921) in period three after the financial crisis. Thus, FF5 captures returns with high performance in period three. Explanation power and the performance of FF5 increases significantly after the financial crisis based on size and BE/ME portfolio sorts.

5.2.3 Factor loadings

Below on tables four, five and six, the regression outcomes from tests on size and book-to-market are reported. First, evaluation of risk factor coefficients takes a view on joint examination of all coefficients. All market and size factor coefficients are statistically significant in all the tables showing the importance of these risk factors in the asset pricing models. Average absolute SMB coefficients have lowered from the control period (0.603) to period two (0.571) but increased again strongly in period three (0.613). This increase on average absolute slopes results from the increased positive explanatory power of SMB in the smallest size column in period three. This fact and increase of SMB explanatory power can be a result of the relatively much lower number of small firms after the financial crisis. The financial crisis seems to be wiped out a large number of small firms (which most surely are junk firms on average). This lower number of small firms seems to increase SMB positive explanation power on smallest size quantile, increasing the size effect on lowest market capital firms.

Table 4. Period one: regressions on portfolios formed on size and book-to-market (01/1989 - 12/1998)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a

	Small Size	2	3	4	Big Size
Low B/M	-0,035	-0,006	0,006	0,010	0,011
2	0,000	-0,004	-0,002	-0,003	-0,006
3	0,003	0,003	0,000	-0,012	-0,006
4	0,016	0,010	0,000	-0,001	-0,016
High B/M	0,013	0,000	-0,002	-0,006	-0,007

t(a)

	Small Size	2	3	4	Big Size
Low B/M	-5,658	-1,168	1,081	1,490	2,721
2	0,044	-0,798	-0,283	-0,554	-1,164
3	0,517	0,679	-0,009	-2,167	-0,972
4	3,189	2,105	0,059	-0,229	-2,975
High B/M	2,955	0,034	-0,256	-0,795	-0,785

b

	Small Size	2	3	4	Big Size
Low B/M	1,081	1,170	1,128	1,015	0,926
2	0,973	1,000	1,057	1,013	0,985
3	0,862	0,908	0,960	1,042	1,023
4	0,792	0,922	0,943	0,926	1,066
High B/M	0,851	1,061	1,054	1,045	1,251

t(b)

	Small Size	2	3	4	Big Size
Low B/M	93,107	119,640	98,931	80,429	119,494
2	89,206	109,208	98,836	96,047	99,911
3	83,938	107,136	97,497	100,893	93,592
4	84,479	104,831	98,653	93,454	104,134
High B/M	101,943	99,773	88,292	74,092	75,039

s

	Small Size	2	3	4	Big Size
Low B/M	1,066	1,061	0,788	0,353	-0,292
2	0,988	0,938	0,761	0,342	-0,200
3	0,869	0,825	0,629	0,378	-0,264
4	0,806	0,815	0,607	0,218	-0,163
High B/M	0,841	0,880	0,624	0,318	-0,070

t(s)

	Small Size	2	3	4	Big Size
Low B/M	65,517	77,385	49,306	19,962	-26,917
2	64,579	73,071	50,733	23,139	-14,454
3	60,359	69,419	45,590	26,076	-17,231
4	61,300	66,073	45,238	15,692	-11,326
High B/M	71,859	59,010	37,254	16,080	-3,011

h

	Small Size	2	3	4	Big Size
Low B/M	-0,285	-0,356	-0,348	-0,286	-0,484
2	-0,037	0,014	0,100	0,154	-0,020
3	0,082	0,211	0,353	0,420	0,186
4	0,206	0,374	0,425	0,472	0,671
High B/M	0,322	0,509	0,571	0,731	1,245

t(h)

	Small Size	2	3	4	Big Size
Low B/M	-12,141	-18,051	-15,129	-11,207	-30,952
2	-1,702	0,733	4,630	7,238	-1,018
3	3,970	12,331	17,744	20,160	8,434
4	10,880	21,088	21,992	23,594	32,443
High B/M	19,085	23,690	23,692	25,651	36,991

r

	Small Size	2	3	4	Big Size
Low B/M	-0,404	-0,337	-0,357	-0,353	0,389
2	-0,211	-0,091	-0,040	-0,155	0,043
3	-0,111	0,045	-0,012	-0,005	-0,254
4	-0,052	0,067	0,091	0,027	-0,068
High B/M	-0,039	0,029	0,032	-0,047	-0,149

t(r)

	Small Size	2	3	4	Big Size
Low B/M	-14,794	-14,664	-13,322	-11,893	21,316
2	-8,223	-4,207	-1,571	-6,262	1,860
3	-4,578	2,280	-0,538	-0,218	-9,888
4	-2,337	3,218	4,065	1,166	-2,829
High B/M	-1,967	1,167	1,137	-1,408	-3,803

c

	Small Size	2	3	4	Big Size
Low B/M	0,152	-0,209	-0,425	-0,447	-0,028
2	0,121	-0,060	-0,158	-0,065	0,089
3	0,108	0,019	-0,076	-0,040	0,315
4	0,091	0,033	-0,009	0,024	-0,083
High B/M	0,124	0,055	0,030	-0,101	-0,418

t(c)

	Small Size	2	3	4	Big Size
Low B/M	5,967	-9,749	-17,045	-16,186	-1,645
2	5,051	-2,987	-6,747	-2,816	4,146
3	4,797	1,005	-3,543	-1,758	13,160
4	4,437	1,724	-0,450	1,119	-3,682
High B/M	6,772	2,360	1,155	-3,275	-11,463

Table four contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and book-to-market in control period of (01/1989 – 12/1998). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Book-to-market level increases from up to bottom from low book-to-market firms on the first quantile to the high book-to-market firms in the last quantile. The book-to-market ratio is calculated by dividing the book value of assets by the market value of the assets. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

Table 5. Period two: regressions on portfolios formed on size and book-to-market (01/1999 - 12/2008)

$$R_i - R_{ft} = a_i + b_iMKT_t + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size	t(a)	Small Size	2	3	4	Big Size
Low B/M	-0,027	-0,009	0,004	0,036	0,000	Low B/M	-2,439	-1,182	0,521	3,900	0,125
2	0,005	-0,001	0,011	0,006	0,003	2	0,504	-0,207	1,534	0,701	0,408
3	-0,002	0,002	0,001	-0,008	0,000	3	-0,346	0,340	0,099	-0,811	-0,028
4	0,019	-0,003	-0,003	0,007	-0,027	4	2,964	-0,496	-0,335	0,733	-2,619
High B/M	0,008	-0,011	0,026	-0,008	-0,004	High B/M	1,205	-1,384	2,450	-0,579	-0,288

b	Small Size	2	3	4	Big Size	t(b)	Small Size	2	3	4	Big Size
Low B/M	0,967	1,058	1,041	1,017	0,969	Low B/M	99,426	168,335	140,058	125,127	279,174
2	0,932	1,061	0,980	0,977	1,012	2	117,392	179,072	155,559	137,882	149,965
3	0,862	1,030	0,998	1,018	0,986	3	142,100	177,236	142,487	121,352	124,269
4	0,808	1,041	0,990	0,988	1,076	4	140,705	184,899	136,685	121,956	119,283
High B/M	0,812	1,121	1,062	1,080	1,070	High B/M	142,290	166,131	115,511	95,357	90,746

s	Small Size	2	3	4	Big Size	t(s)	Small Size	2	3	4	Big Size
Low B/M	1,020	0,956	0,656	0,314	-0,196	Low B/M	55,367	80,251	46,560	20,386	-29,722
2	1,028	0,986	0,611	0,229	-0,163	2	68,334	87,839	51,214	17,042	-12,764
3	0,907	0,939	0,568	0,232	-0,160	3	78,872	85,294	42,757	14,579	-10,662
4	0,874	0,944	0,498	0,223	-0,163	4	80,298	88,447	36,319	14,538	-9,530
High B/M	0,865	0,996	0,482	0,093	-0,163	High B/M	79,970	77,887	27,643	4,341	-7,312

h	Small Size	2	3	4	Big Size	t(h)	Small Size	2	3	4	Big Size
Low B/M	-0,081	-0,217	-0,302	-0,285	-0,295	Low B/M	-4,344	-18,114	-21,306	-18,360	-44,467
2	0,037	0,020	0,028	0,080	0,068	2	2,473	1,731	2,342	5,931	5,303
3	0,184	0,173	0,240	0,270	0,350	3	15,899	15,589	17,958	16,852	23,082
4	0,279	0,337	0,309	0,480	0,964	4	25,482	31,339	22,371	31,054	55,982
High B/M	0,431	0,624	0,739	0,901	1,220	High B/M	39,577	48,449	42,082	41,671	54,203

r	Small Size	2	3	4	Big Size	t(r)	Small Size	2	3	4	Big Size
Low B/M	-0,411	-0,367	-0,426	-0,471	0,085	Low B/M	-19,084	-26,366	-25,854	-26,168	11,035
2	-0,191	0,059	0,037	0,076	0,203	2	-10,888	4,517	2,617	4,869	13,606
3	0,039	0,175	0,162	0,192	0,186	3	2,900	13,573	10,467	10,355	10,580
4	0,011	0,155	0,152	0,054	-0,043	4	0,892	12,420	9,451	2,997	-2,137
High B/M	-0,001	0,069	-0,128	-0,247	-0,341	High B/M	-0,115	4,631	-6,276	-9,838	-13,042

c	Small Size	2	3	4	Big Size	t(c)	Small Size	2	3	4	Big Size
Low B/M	0,151	0,017	-0,201	-0,224	0,007	Low B/M	5,727	1,022	-9,963	-10,158	0,724
2	0,172	0,107	0,020	0,286	0,328	2	7,991	6,635	1,177	14,876	17,902
3	0,157	0,110	0,083	0,284	0,221	3	9,555	6,963	4,338	12,453	10,271
4	0,101	0,084	0,231	0,260	0,038	4	6,467	5,498	11,757	11,818	1,566
High B/M	0,093	0,043	0,061	0,173	-0,149	High B/M	6,028	2,358	2,458	5,607	-4,663

Table five contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and book-to-market in period two of (01/1999 – 12/2008). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Book-to-market level increases from up to bottom from low book-to-market firms on the first quantile to the high book-to-market firms in the last quantile. The book-to-market ratio is calculated by dividing the book value of assets by the market value of the assets. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

Table 6. Period three: regressions on portfolios formed on size and book-to-market (01/2009 - 12/2018)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size	t(a)	Small Size	2	3	4	Big Size
Low B/M	-0,014	0,007	0,002	0,009	0,003	Low B/M	-1,593	1,246	0,328	1,557	1,021
2	0,000	0,007	0,004	0,004	-0,001	2	0,002	1,507	0,778	0,771	-0,308
3	-0,001	0,000	-0,003	-0,003	0,001	3	-0,158	0,076	-0,632	-0,396	0,185
4	0,003	-0,008	0,005	0,001	-0,005	4	0,450	-1,780	0,888	0,192	-0,801
High B/M	0,009	-0,005	-0,005	0,006	0,001	High B/M	1,794	-0,859	-0,598	0,742	0,117

b	Small Size	2	3	4	Big Size	t(b)	Small Size	2	3	4	Big Size
Low B/M	0,961	1,036	1,048	1,041	0,995	Low B/M	97,621	155,194	154,384	157,423	277,826
2	0,951	1,027	1,036	1,050	0,984	2	114,153	178,353	176,282	162,244	215,159
3	0,926	1,020	1,023	1,082	0,996	3	134,701	198,901	162,792	145,564	171,870
4	0,892	0,988	0,999	1,014	0,968	4	125,533	188,311	148,252	135,941	139,101
High B/M	0,838	1,085	1,030	1,055	1,109	High B/M	140,547	154,763	115,154	122,016	102,686

s	Small Size	2	3	4	Big Size	t(s)	Small Size	2	3	4	Big Size
Low B/M	1,091	0,965	0,643	0,279	-0,154	Low B/M	63,475	82,850	54,258	24,151	-24,604
2	1,104	0,952	0,616	0,264	-0,142	2	75,886	94,701	60,000	23,408	-17,846
3	1,080	0,945	0,603	0,288	-0,174	3	89,976	105,534	54,926	22,153	-17,166
4	1,102	0,934	0,595	0,252	-0,194	4	88,850	101,994	50,558	19,370	-15,967
High B/M	1,003	0,985	0,587	0,237	-0,123	High B/M	96,348	80,493	37,599	15,727	-6,502

h	Small Size	2	3	4	Big Size	t(h)	Small Size	2	3	4	Big Size
Low B/M	-0,297	-0,409	-0,368	-0,306	-0,315	Low B/M	-17,527	-35,623	-31,469	-26,913	-51,076
2	-0,186	-0,147	-0,079	-0,132	-0,054	2	-12,942	-14,798	-7,773	-11,839	-6,860
3	0,037	0,144	0,108	0,133	0,126	3	3,156	16,323	9,956	10,361	12,676
4	0,308	0,363	0,312	0,368	0,707	4	25,177	40,194	26,901	28,664	58,965
High B/M	0,414	0,611	0,624	0,724	1,101	High B/M	40,312	50,632	40,540	48,637	59,228

r	Small Size	2	3	4	Big Size	t(r)	Small Size	2	3	4	Big Size
Low B/M	-0,656	-0,469	-0,267	-0,093	0,108	Low B/M	-23,141	-24,425	-13,666	-4,884	10,475
2	-0,466	-0,090	0,047	0,030	0,122	2	-19,412	-5,452	2,761	1,595	9,290
3	-0,135	0,090	0,099	0,080	-0,013	3	-6,832	6,090	5,454	3,759	-0,772
4	-0,036	0,144	0,052	0,064	-0,007	4	-1,744	9,512	2,685	2,957	-0,356
High B/M	-0,010	0,014	-0,064	-0,139	-0,656	High B/M	-0,592	0,708	-2,477	-5,588	-21,096

c	Small Size	2	3	4	Big Size	t(c)	Small Size	2	3	4	Big Size
Low B/M	-0,180	-0,246	-0,234	-0,043	-0,157	Low B/M	-5,657	-11,372	-10,664	-2,009	-13,579
2	-0,157	-0,047	0,063	0,161	0,091	2	-5,818	-2,518	3,292	7,698	6,146
3	0,002	0,043	0,114	0,113	0,209	3	0,104	2,569	5,630	4,716	11,128
4	-0,065	0,011	0,141	0,033	-0,206	4	-2,846	0,668	6,472	1,353	-9,127
High B/M	0,073	0,089	0,164	-0,071	-0,520	High B/M	3,808	3,928	5,668	-2,551	-14,874

Table six contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and book-to-market in period three of (01/2009 – 12/2018). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Book-to-market level increases from up to bottom from low book-to-market firms on the first quantile to the high book-to-market firms in the last quantile. The book-to-market ratio is calculated by dividing the book value of assets by the market value of the assets. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

On other size columns, coming to the present-day SMB has lost slightly its explanatory power pushing it towards zero. This supports the importance of size factor in explaining returns of the smallest firms, but on explaining returns of firms on other size columns factor seems to lose its power steadily. This is in line what was seen on the average return patterns in (table 2.c) on the smallest size column. The importance of market factor positive explanatory power also has increased with excess returns, as the coefficients in the period three (table 6) on average were (1.006) as the period two (table 5) average is (0.998).

Evaluating the home sort risk-factor, the value, in this case, shows that value factor has been steady in the period one and two decreasing coming to period three. These results are similar to what was seen on average return patterns as on the period three BE/ME effect seems to reverse. On absolute average terms, HML (value) coefficient has lowered from period two (0.357) with 24 significant coefficients to period three (0.335) with 25 significant coefficients. This drop of six percentage of explanation power on average absolute coefficients of HML factor is big and significant since absolute value was (0.354) on control period with 20 significant coefficients. Showing the HML factor was steady and increasing between the control period and period two, suffering drop after financial crisis breakpoint. On average absolute terms, RMW and CMA have had the lowest coefficients on the control period (0.136, 0.131), increasing highly to second period (0.171, 0.144) and again dropping to the value of (0.158, 0.129). With RMW and CMA having significant coefficients between 20 - 23 in the last two periods.

Second, in the straight coefficient comparison, extreme sorts are used mainly because those provide significant coefficients in all periods studied in this thesis and thus allow direct comparison. On profitability and investment coefficient comparison, there seem to be some trends that can be seen. In RMW coefficients firms in smallest size column with the lowest BE/ME, rows seem to be unprofitable in all periods, but in the last period, negative coefficients (robust profitability) decreases significantly more. Showing that small-sized low BE/ME firms are very unprofitable on average at period three. However, as size increases to biggest size column, these firms on the lowest BE/ME category have positive coefficient throughout the periods, and negative coefficients of RMW on high BE/ME row directly opposite to small firms' column.

Highest BE/ME row seems to have weak profitability throughout time, which decreases almost half (-0.341) to (-0.656) from period two to period three. The period after the financial crisis (table 6) seems to hit firms in the extreme categories of size and BE/ME very hard in terms of profitability.

On CMA comparison, the biggest changes are visible again in the extreme size columns. On the column of small firms at the control and the second period, the positive CMA coefficient has been on average (0.119) at the control period slightly increasing to period two (0.135). This average coefficient drops to (-0.065) on period three, suggesting small firms making more aggressive investing than in the first two periods. On other size columns, the investment factor coefficients seem to variate highly, and statistically significant coefficients that are found from two lowest BE/ME rows are mostly negative in the control period. On period two, there are many positive statistically significant coefficients in the table, and this positive relation lowers but stays in period three, excluding the lowest BE/ME row and smallest size column. Firms on the lowest BE/ME row, growth firms seem to invest aggressively, which leads to negative coefficients. Lowest BE/ME row firms are also unprofitable on average based on what is seen on RMW factor loadings. The similar story is seen on the biggest size column, and highest BE/ME row as firms in that category seem to invest aggressively despite low profitability (RMW -0.656 and CMA -0.520).

On the first two periods, low average returns of firms on low BE/ME portfolios are clearly seen. Still, average returns of low BE/ME firms on the period three are good on relative comparison suggesting the market has changed after the financial crisis on this term and drivers of good returns of growth firms in the period three are on somewhere else than in the robust profitability or conservative investing activities. To conclude lowest BE/ME row firms seem to be unprofitable and invest aggressively, which definitely is one driver behind the BE/ME and value effect. Still, this fact of low profitability and aggressive investing seems not to have an effect on the average returns of these firms.

SMB factor has been steady in the first two periods in the smallest size column increasing above one on period three as pointed out earlier in the joint examination. SMB coefficient increases slightly coming from second to last period in the three highest BE/ME rows on all size columns. Mostly on size columns three (0.482 to 0.587) and four (0.093 to 0.237). Two lowest BE/ME rows have a steady increase over the second and last period. In biggest size column, on comparison of SMB average, negative slopes increase steadily as on the control period the average slope is (-0.198), (-0.169) on second and on third (-0.157). SMB trend is visible as explanatory power increases in small firms over the coefficient of one and decreases towards zero on big firms. HML factor coefficients are pretty steady in the lowest and highest BE/ME rows through periods. Firms on lowest BE/ME rows having negative coefficients and firms on the highest BE/ME rows having strongly positive coefficients. Single HML factor coefficients do not variate too much around periods, but lower importance is seen on joint examination. There are a couple more negative coefficients on the third period compared to second which signs about lowering importance of positive explanation power on excess returns of BE/ME. High BE/ME firms are much more explanatory with HML factor than lower BE/ME firms having twice as high absolute coefficients.

5.2.4 Highlights on size and book-to-market tests

Lowering dispersion in returns on different sorts on size and BE/ME signs lower importance of BE/ME effect on the period after the financial crisis in explaining differences in average returns. This is in line with Kothari et. al (1995) critics as they argued that BE/ME significance may variate in different states. What comes to value factor and its importance on asset pricing, we need to remember that these are the size and BE/ME sorts only. BE/ME does not fully reflect the value effect, only some part of it. Other ratios and characteristics of firms such as P/E, P/C also play the main role in value effect and importance of quality on value investing has been brought up by many studies (e.g. Novy-Marx, 2013, Asness et al. 2019).

From regression performance statics on size and BE/ME tests, it is easy to see that average excess returns on these portfolios are significantly more explanatory with different risk factor returns in present day and last ten years than in the 1990 - 2008 at the U.S. equity market. FF5 performance had significant improvements on performance statics between the period two and period three.

Coefficients on the HML risk factor reveals a drop of six percentage on explanation power after the financial crisis breakpoint. This is significant as results show that HML factor was pretty steady and increasing between the periods one and two. The financial crisis and changes in the market resulted in a drop on explanation power of the HML factor. Regression tests also reveal that high BE/ME firms are much more explanatory with HML factor than lower BE/ME firms. High BE/ME firms having twice higher absolute average coefficients than low BE/ME firms. Growth firms (low BE/ME) seem to invest aggressively and unprofitable based on factor loadings, which surely have been one driver behind differences in value and growth firms' average returns. Large differences in average returns between value and growth firms have been seen on the first two periods, as the value was delivering higher average returns. On period three, this difference vanishes and returns of growth firms are good in relative comparison. This suggests that markets and the risk factor have changed after the financial crisis on this term and drivers of a good return on growth firms are on somewhere else than in straight profitability or conservative investing activities. Maybe the return expectations on growth firms have increased, good investment opportunities decreased, or markets trust on BE/ME effect delivering better returns decreased. Whatever the explanation, the results are straightforward in this case.

Interesting findings were also made on SMB factor coefficients. SMB coefficients seem to increase on small firms and decrease towards zero on big firms. The profitability of small firms has decreased at the same time as the SMB has increased. Seems like liquidity premium between different sized firms have increased on period three based on these results. Thus, SMB is much more effective in explaining the returns of small firms compared to big sized firms.

What we can conclude is that BE/ME differentiation power in average returns is affected by different states and straight size effect on average returns seems to be visible on these sorts only on the second period. This is in line with low size importance found in empirical studies. But as Asness et al. (2018) argue that size effect is visible only if junk or quality characteristics are controlled. To answer this, 2x4x4 sorts should control better for quality characteristics that could bring size effect more visible.

5.3 Tests on Size and Operating Profitability Portfolios

Tests on the size and operating profitability on 5x5 sorted portfolios are evaluated in this subchapter. The subchapter structure is similar to the previous, tests on size and book-to-market.

5.3.1 Return patterns

Table 7.a Period one: Average daily returns on (SIZE&OP) 01/1989 - 12/1998

	Small Size	2	3	4	Big Size
Low OP	0,025	0,035	0,049	0,045	0,079
2	0,057	0,054	0,059	0,057	0,064
3	0,061	0,061	0,058	0,060	0,068
4	0,052	0,051	0,062	0,068	0,072
High OP	0,055	0,070	0,063	0,062	0,085

Table 7.b Period two: Average daily returns on (SIZE&OP) 01/1999 - 12/2008

	Small Size	2	3	4	Big Size
Low OP	0,025	0,003	0,006	0,013	-0,035
2	0,050	0,042	0,032	0,028	-0,001
3	0,048	0,043	0,032	0,019	0,006
4	0,049	0,053	0,036	0,034	0,007
High OP	0,036	0,043	0,043	0,038	0,011

Table 7.c Period three: Average daily returns on (SIZE&OP) 01/2009 - 12/2018

	Small Size	2	3	4	Big Size
Low OP	0,049	0,065	0,058	0,057	0,056
2	0,061	0,052	0,060	0,067	0,048
3	0,051	0,061	0,060	0,065	0,055
4	0,062	0,055	0,057	0,063	0,056
High OP	0,049	0,064	0,063	0,064	0,056

Table seven presents average daily returns for 25 portfolios sorted by size measured as market capitalization and the operating profitability for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis).

The average returns in the control period (table 7.a) follow strict risk factor patterns as operating profitability increases the average returns increase in each size columns. The only exception to the systematic pattern is a relatively high return on the biggest size column and lowest operating profitability row. The high average return of these firms is interesting as regression coefficients reveal that firms in this category are highly unprofitable and invest aggressively (regression coefficients discussed later). Size related return pattern is not visible in this period and sort.

The return patterns in period two (table 7.b) tell much of the same story that was seen on the control period. Operating profitability patterns are very visible in all categories except for the smallest size column that has similar returns in three middle operating profitability rows and lowest returns on the extremes. Size effect patterns are visible in the second period as returns increase as size column decreases. This result is similar to what was found on size and BE/ME sorts. Biggest size column has close to zero returns in all operating profitability rows. Return patterns on period three (table 7.c) are very similar to sorts made on size and BE/ME. There are no clear and strong size or operating profitability effect on average returns on period three. Dispersion of daily returns is again small (0.049 - 0.065), and all categories seem to have similar returns.

Differences between the (01/1999 - 12/2008) and (01/2009 - 12/2018) seem significant also in portfolio sorts made by size and operating profitability. Size and operating profitability effect seem to lose its power in differentiating returns coming to the period after the financial crisis as all stocks in each category seem to have similar returns no matter the differences on these characteristics. Dispersion of returns on different twenty-five categories is only (0.016) after the financial crisis as in first-period dispersion is (0.06) and on second (0.088). These differences between periods are huge and significant as daily returns are used. This supports the previous empirical findings that risk factors lose much of their powers in some market states.

5.3.2 Performance of FF5

Performance statistics are reported below in table eight. Performance measured as adjusted R^2 values and intercept values is again weakest in the control period (table 8.a). Average R^2 is (0.882), and dispersion is high at (0.148) between the lowest and highest value. Absolute intercept is (0.006), and in twenty-five regressions, there were six significant intercepts in a 95 % confidence level t-test. Significant values (5) were mostly found in the two lowest size columns. Performance increases coming to period two. Average R^2 increases to (0.919) and R^2 dispersion lowers to (0.099). There are less significant intercept values (2) than in the control period, but the absolute average intercept value is a bit higher on (0.008).

Table 8.a Period one: Adjusted R^2 values for regression (SIZE&OP) 01/1989 - 12/1998

	Small Size	2	3	4	Big Size
Low OP	0,893	0,924	0,882	0,832	0,863
2	0,860	0,892	0,871	0,847	0,884
3	0,831	0,890	0,882	0,878	0,895
4	0,813	0,894	0,894	0,891	0,948
High OP	0,853	0,911	0,889	0,878	0,962

Table 8.b Period two: Adjusted R^2 values for regression (SIZE&OP) 01/1999 - 12/2008

	Small Size	2	3	4	Big Size
Low OP	0,913	0,968	0,932	0,921	0,929
2	0,928	0,949	0,919	0,897	0,880
3	0,915	0,936	0,927	0,906	0,911
4	0,909	0,949	0,917	0,896	0,940
High OP	0,869	0,933	0,893	0,890	0,948

Table 8.c Period three: Adjusted R^2 values for regression (SIZE&OP) 01/2009 - 12/2018

	Small Size	2	3	4	Big Size
Low OP	0,956	0,973	0,932	0,919	0,930
2	0,954	0,973	0,959	0,948	0,954
3	0,943	0,972	0,958	0,944	0,951
4	0,943	0,964	0,955	0,940	0,971
High OP	0,927	0,960	0,943	0,934	0,965

Table eight presents the adjusted R^2 values of the 25 regressions made to portfolios sorted on size measured as market capitalization and operating profitability for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis). For a detailed description of the adjusted R^2 value check the first part of chapter 4. Asset pricing models.

Period three (table 8.c) has once again the steadiest and the highest performance statistics of the FF5 model. Average R^2 is very high at (0.951) and dispersion as low as (0.054). Average intercept is (0.004) with zero significant values. Two of the intercept values were close to being statistically significant, but slightly under the 95 % confidence level on t-test. FF5 model performs much better and steadier after the financial crisis, which is in line to findings in size and book-to-market tests.

5.3.3 Factor loadings

Below on tables nine, ten and eleven, the regression outcomes from tests on size and operating profitability are reported. First starting with the joint examination of coefficients. The absolute average profitability coefficient increases highly over sixteen percentage from the control period (0.269) with 21 significant coefficients, at (0.313) on the second period with 24 significant coefficients. Increase to period three is (0.328) with 24 significant coefficients.

Table 9. Period one: regressions on portfolios formed on size and operating profitability (01/1989 - 12/1998)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size
Low OP	-0,018	-0,014	0,002	-0,003	0,024
2	0,010	0,003	0,007	0,001	0,000
3	0,012	0,008	-0,001	-0,003	-0,002
4	0,001	-0,004	0,003	0,003	-0,008
High OP	0,002	0,010	0,000	-0,004	0,005

t(a)	Small Size	2	3	4	Big Size
Low OP	-3,498	-2,574	0,300	-0,440	3,413
2	2,188	0,673	1,292	0,220	-0,078
3	2,248	1,724	-0,159	-0,606	-0,425
4	0,125	-0,893	0,523	0,538	-1,867
High OP	0,315	2,044	0,009	-0,687	1,292

b	Small Size	2	3	4	Big Size
Low OP	0,994	1,194	1,111	0,963	1,035
2	0,838	0,952	0,982	0,935	1,011
3	0,843	0,931	0,984	0,979	0,958
4	0,894	0,983	1,036	1,017	1,032
High OP	0,974	1,104	1,091	1,080	0,965

t(b)	Small Size	2	3	4	Big Size
Low OP	102,234	117,090	88,875	72,707	78,475
2	94,800	106,798	92,948	82,883	93,948
3	86,574	106,791	101,885	99,477	94,649
4	81,267	107,488	105,555	101,714	133,513
High OP	90,669	116,310	99,985	94,968	136,838

s	Small Size	2	3	4	Big Size
Low OP	0,978	0,994	0,624	0,264	-0,151
2	0,843	0,827	0,613	0,286	-0,177
3	0,845	0,861	0,664	0,300	-0,287
4	0,921	0,949	0,762	0,323	-0,237
High OP	0,997	1,076	0,831	0,420	-0,257

t(s)	Small Size	2	3	4	Big Size
Low OP	71,769	69,536	35,618	14,219	-8,144
2	68,021	66,163	41,359	18,072	-11,723
3	61,894	70,413	49,029	21,719	-20,206
4	59,651	74,005	55,363	23,007	-21,859
High OP	66,165	80,866	54,302	26,350	-25,934

h	Small Size	2	3	4	Big Size
Low OP	-0,116	-0,231	-0,153	-0,017	0,215
2	0,125	0,118	0,118	0,150	0,207
3	0,181	0,151	0,184	0,238	0,071
4	0,157	0,210	0,225	0,209	0,074
High OP	0,098	0,123	0,155	0,232	-0,265

t(h)	Small Size	2	3	4	Big Size
Low OP	-5,891	-11,235	-6,046	-0,649	8,062
2	7,016	6,533	5,539	6,577	9,542
3	9,219	8,553	9,460	11,961	3,485
4	7,087	11,384	11,363	10,333	4,766
High OP	4,507	6,400	7,044	10,109	-18,629

r	Small Size	2	3	4	Big Size
Low OP	-0,450	-0,547	-0,718	-0,700	-0,953
2	-0,083	-0,104	-0,308	-0,319	-0,592
3	0,041	0,070	0,036	-0,097	-0,254
4	0,069	0,143	0,073	-0,007	0,141
High OP	0,077	0,220	0,205	0,000	0,524

t(r)	Small Size	2	3	4	Big Size
Low OP	-19,666	-22,779	-24,421	-22,437	-30,690
2	-3,984	-4,962	-12,394	-12,009	-23,380
3	1,778	3,398	1,600	-4,185	-10,660
4	2,666	6,659	3,137	-0,308	7,733
High OP	3,063	9,858	7,963	0,016	31,587

c	Small Size	2	3	4	Big Size
Low OP	0,211	0,042	-0,158	-0,165	-0,271
2	0,099	-0,009	-0,141	-0,141	0,118
3	0,075	-0,020	-0,109	-0,069	0,224
4	0,121	-0,117	-0,226	-0,176	0,038
High OP	0,087	-0,076	-0,254	-0,263	-0,012

t(c)	Small Size	2	3	4	Big Size
Low OP	9,922	1,898	-5,779	-5,687	-9,395
2	5,111	-0,474	-6,088	-5,690	4,998
3	3,527	-1,053	-5,167	-3,217	10,114
4	5,016	-5,834	-10,505	-8,024	2,251
High OP	3,686	-3,649	-10,651	-10,570	-0,778

Table nine contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and operating profitability in control period of (01/1989 – 12/1998). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Operating profitability increases from up to bottom from low operating profitability firms on the first quantile to the high operating profitability firms in the last quantile. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

Table 10. Period two: regressions on portfolios formed on size and operating profitability (01/1999 - 12/2008)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size
Low OP	-0,002	-0,017	0,013	0,027	-0,009
2	0,008	0,004	0,006	0,020	-0,005
3	0,004	0,002	0,003	-0,003	0,007
4	0,006	0,008	0,007	0,008	0,003
High OP	-0,005	0,000	0,011	0,016	-0,003

t(a)	Small Size	2	3	4	Big Size
Low OP	-0,280	-2,686	1,317	2,519	-0,885
2	1,188	0,666	0,746	1,993	-0,536
3	0,540	0,322	0,363	-0,359	0,800
4	0,810	1,223	0,893	1,030	0,469
High OP	-0,595	0,032	1,248	1,699	-0,554

b	Small Size	2	3	4	Big Size
Low OP	0,895	1,126	1,079	1,099	1,049
2	0,845	1,027	1,000	1,021	0,992
3	0,827	1,029	0,977	0,967	1,039
4	0,832	1,038	0,964	0,964	0,993
High OP	0,884	1,038	1,025	1,023	1,000

t(b)	Small Size	2	3	4	Big Size
Low OP	117,013	201,327	123,469	119,107	119,905
2	148,924	180,040	145,114	119,250	113,945
3	137,737	164,726	156,978	139,423	132,563
4	134,159	184,967	144,790	135,393	167,884
High OP	109,327	161,178	128,424	126,479	193,358

s	Small Size	2	3	4	Big Size
Low OP	0,970	1,011	0,597	0,230	-0,253
2	0,884	0,918	0,565	0,218	-0,228
3	0,877	0,925	0,571	0,218	-0,247
4	0,864	0,996	0,599	0,247	-0,161
High OP	0,900	0,955	0,627	0,346	-0,129

t(s)	Small Size	2	3	4	Big Size
Low OP	66,858	95,423	36,024	13,164	-15,249
2	82,124	84,861	43,290	13,432	-13,836
3	77,133	78,144	48,385	16,573	-16,615
4	73,444	93,605	47,497	18,331	-14,407
High OP	58,741	78,239	41,464	22,564	-13,169

h	Small Size	2	3	4	Big Size
Low OP	0,014	-0,078	-0,145	-0,019	0,423
2	0,352	0,203	0,123	0,154	0,171
3	0,406	0,226	0,173	0,245	0,057
4	0,329	0,272	0,200	0,127	-0,034
High OP	0,267	0,240	0,126	0,111	-0,157

t(h)	Small Size	2	3	4	Big Size
Low OP	0,990	-7,276	-8,665	-1,087	25,340
2	32,449	18,610	9,352	9,413	10,292
3	35,474	18,961	14,600	18,487	3,818
4	27,769	25,356	15,725	9,373	-2,987
High OP	17,284	19,520	8,280	7,200	-15,940

r	Small Size	2	3	4	Big Size
Low OP	-0,415	-0,503	-0,888	-0,893	-0,982
2	0,122	0,054	0,010	-0,392	-0,235
3	0,227	0,205	0,143	0,060	-0,132
4	0,253	0,309	0,176	0,198	0,192
High OP	0,235	0,342	0,269	0,128	0,469

t(r)	Small Size	2	3	4	Big Size
Low OP	-24,483	-40,619	-45,853	-43,687	-50,682
2	9,703	4,241	0,687	-20,636	-12,203
3	17,096	14,811	10,394	3,894	-7,628
4	18,401	24,840	11,963	12,544	14,664
High OP	13,129	23,943	15,192	7,159	40,975

c	Small Size	2	3	4	Big Size
Low OP	0,293	0,195	-0,021	-0,011	-0,398
2	0,035	0,080	0,109	0,155	0,264
3	-0,026	0,030	0,041	0,131	0,051
4	-0,010	-0,028	-0,103	0,186	-0,138
High OP	-0,032	-0,121	-0,051	0,046	0,091

t(c)	Small Size	2	3	4	Big Size
Low OP	14,095	12,809	-0,891	-0,427	-16,765
2	2,294	5,133	5,830	6,651	11,178
3	-1,581	1,793	2,429	6,964	2,417
4	-0,579	-1,856	-5,694	9,618	-8,575
High OP	-1,443	-6,909	-2,337	2,075	6,457

Table ten contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and operating profitability in period two of (01/1999 – 12/2008). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Operating profitability increases from up to bottom from low operating profitability firms on the first quantile to the high operating profitability firms in the last quantile. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

Table 11. Period three: regressions on portfolios formed on size and operating profitability (01/2009 - 12/2018)

$$R_i - R_{ft} = \ a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size
Low OP	-0,004	0,004	-0,001	-0,003	0,001
2	0,011	-0,004	0,004	0,011	-0,006
3	0,001	0,004	0,002	0,008	0,001
4	0,009	-0,004	-0,003	0,003	0,001
High OP	-0,009	0,000	0,000	0,004	-0,001

t(a)	Small Size	2	3	4	Big Size
Low OP	-0,649	0,846	-0,095	-0,372	0,172
2	1,957	-0,972	0,712	1,863	-1,115
3	0,133	0,838	0,398	1,340	0,280
4	1,385	-0,851	-0,485	0,598	0,331
High OP	-1,178	-0,035	-0,009	0,601	-0,152

b	Small Size	2	3	4	Big Size
Low OP	0,916	1,074	1,063	1,108	1,085
2	0,866	0,984	0,989	1,025	1,018
3	0,869	0,987	1,004	1,031	0,982
4	0,895	1,011	1,035	1,040	0,977
High OP	0,991	1,081	1,066	1,049	0,985

t(b)	Small Size	2	3	4	Big Size
Low OP	130,514	178,146	118,626	116,315	123,522
2	129,992	188,685	165,295	156,464	171,986
3	115,088	185,515	168,392	155,209	181,385
4	117,706	166,374	164,029	156,862	243,930
High OP	108,753	165,644	149,817	149,852	233,082

s	Small Size	2	3	4	Big Size
Low OP	1,058	0,956	0,605	0,280	-0,178
2	1,029	0,930	0,601	0,253	-0,195
3	1,078	0,952	0,596	0,236	-0,151
4	1,109	0,979	0,635	0,274	-0,155
High OP	1,126	0,969	0,638	0,289	-0,142

t(s)	Small Size	2	3	4	Big Size
Low OP	86,254	90,897	38,683	16,837	-11,589
2	88,450	102,230	57,574	22,103	-18,890
3	81,778	102,510	57,241	20,391	-16,007
4	83,548	92,296	57,597	23,667	-22,102
High OP	70,748	85,033	51,321	23,624	-19,276

h	Small Size	2	3	4	Big Size
Low OP	-0,142	-0,236	-0,192	-0,151	0,235
2	0,315	0,209	0,107	0,131	0,150
3	0,397	0,239	0,083	0,143	0,033
4	0,272	0,198	0,150	-0,054	-0,041
High OP	0,213	0,057	0,007	-0,063	-0,136

t(h)	Small Size	2	3	4	Big Size
Low OP	-11,750	-22,752	-12,421	-9,218	15,567
2	27,472	23,262	10,404	11,604	14,688
3	30,553	26,071	8,041	12,528	3,591
4	20,796	18,959	13,792	-4,735	-6,003
High OP	13,572	5,070	0,597	-5,253	-18,705

r	Small Size	2	3	4	Big Size
Low OP	-0,667	-0,845	-0,833	-0,833	-0,972
2	0,044	0,055	-0,085	-0,139	-0,411
3	0,182	0,211	0,117	0,103	-0,011
4	0,179	0,346	0,325	0,184	0,099
High OP	0,279	0,356	0,340	0,236	0,352

t(r)	Small Size	2	3	4	Big Size
Low OP	-32,981	-48,700	-32,305	-30,386	-38,451
2	2,296	3,690	-4,910	-7,358	-24,117
3	8,368	13,764	6,835	5,377	-0,679
4	8,177	19,767	17,864	9,641	8,579
High OP	10,648	18,942	16,590	11,712	28,961

c	Small Size	2	3	4	Big Size
Low OP	-0,047	-0,148	-0,086	-0,053	-0,062
2	-0,095	-0,033	0,045	-0,007	-0,016
3	-0,111	-0,016	0,049	-0,071	0,046
4	0,055	0,007	0,032	0,166	0,042
High OP	0,092	0,042	0,109	0,151	-0,081

t(c)	Small Size	2	3	4	Big Size
Low OP	-2,091	-7,580	-2,961	-1,729	-2,199
2	-4,418	-1,962	2,351	-0,332	-0,834
3	-4,558	-0,907	2,548	-3,305	2,601
4	2,245	0,380	1,552	7,718	3,242
High OP	3,137	1,973	4,727	6,673	-5,906

Table eleven contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and operating profitability in period three of (01/2009 – 12/2018). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Operating profitability increases from up to bottom from low operating profitability firms on the first quantile to the high operating profitability firms in the last quantile. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based of simple t-test.

The increase is around five percentage after the financial crisis, which is not as significant as the earlier increase in absolute average coefficient was three times higher. Although, the high increase in RMW coefficient shows the hints of a trend, as the increasing importance of RMW factor is revealed on the size and operating profitability sorts.

Joint examination of market excess return factor and SMB coefficients show a similar story as seen on the BE/ME sort. MKT and SMB explanation power decreases coming to the second period and increases again in period three. HML factor follows the similar pattern as it is on absolute average terms (0.161) with 24 significant coefficients at control period, increasing to (0.186) with 23 significant coefficients on the second period and again decreasing to (0.158) with 24 significant coefficients at the period three. Absolute CMA coefficient drops from the control period (0.129) with 22 significant coefficients to second (0.106) with 18 significant coefficients and to last (0.067) with 17 significant coefficients. Which is almost twice as high decrease compared to a decrease from the control period to period two. This drop and decrease on significant coefficients are close to suggesting CMA as unimportant risk factor explain returns in this sort at period three. Increase in RMW coefficients can be seen significant also as HML and CMA seem to lose their explanatory powers to the other factors coming from period two to period three on all sorts studied on this thesis.

Second, taking a view on the single coefficients and extreme categories of sorts. SMB factor performs better once again in explaining the returns of firms in smallest size column and decreases closer to zero in the biggest size column coming to last period. HML factor variates highly around the single coefficients on this sort, still providing 23-24 significant coefficients on every period. Most negative HML coefficients are located in the lowest operating profitability row, which is similar to findings in BE/ME sorts as growth firms seem to be unprofitable ones on average. Thus, most of the growth firms can be found from the lowest operating profitability rows on this sort.

As hints are given on the joint examination, CMA (investment factor) changes are large between the first two periods (tables 9,10) and period three (table 11). On the period one (table 9) firms on smallest and biggest size columns seem to have positive loadings on CMA factor excluding the extreme OP rows in the biggest size column, which have negative coefficients to CMA. On period two (table 10) lowest operating profitability firms' row in the smallest and biggest size columns turn more extreme compared to other coefficients. Small firms have positive loadings and big firms highly negative loadings on CMA factor. Coming to the period three (table 10) CMA factor seems to lose its power on explaining returns in size and operating profitability sorts as coefficients turn closer to zero, extreme coefficients disappear, and there are only 17 statistically significant coefficients in the period three.

Size and operating profitability portfolio sort provide visible patterns in the RMW factor loadings as expected. Lowest operating profitability row has highly negative coefficients, which are steady on the three biggest size categories trough periods. Big changes in single coefficients are visible in two smallest size columns as negative coefficients decrease from (-0.415 to -0.667) and (-0.503 to -0.845) between the second (table 10) and third period (table 11). Suggesting small unprofitable firms turn more unprofitable in the third period. On highest operating profitability row, coefficients increase systematically from the control period (table 9) to the third period. Similar as seen in the joint examination. The only expectation is the biggest size column where coefficient at highest operating profitability row lowers throughout the periods. These results show some signs of the increasing importance of profitability factor in explaining average returns. Differences in average returns between low and high profitability firms, however, were very small among different sorts in the third period although regression coefficients reveal many differences between characteristics of these firms on different portfolios of this sort.

5.3.4 Highlights on size and operating profitability tests

Risk factor return patterns disappear in period three also in size and operating profitability sorts. The average returns in period one and two provide strong evidence of the fact that average returns are associated with the operating profitability of the firm. But this profitability effect seems to fade away when comparing average returns on period three. Size effect pattern is visible only in the second period, providing no clear patterns in period one and period three similar to what was seen on the size and BE/ME sorts. Performance statics follows a similar story as seen on BE/ME sorts. On period three, FF5 has much higher performance on explaining the average returns based on all performance statistics of the regression.

The coefficient comparison reveals that profitability factor explanation power has increased highly between the three periods. The highest increase is between the periods one and two. RMW factor is able to increase its power coming to period three, but not with the same magnitude as between two first periods. Increase after the financial crisis on RMW own sort is around five percentage, which is close to similar as decrease of HML on its own sort. I may be that these two factors have changed powers like as Novy-Marx (2013b) points out the importance quality on value investing. However, differences in average returns were almost invisible between low and high investing firms, although regression coefficients reveal many differences between characteristics of these firms on different portfolio sorts.

Other picks from the tests were a high drop of CMA explanation power coming to period three. CMA explanation power decreases around forty percentage between period two and period three, bringing its coefficients on absolute average terms close to zero. On these sorts, CMA has played the most important part in the control period. SMB factor performs better once again in explaining the returns of firms in smallest size column and decreases closer to zero in the biggest size column coming to period three.

Profitability can be seen as one part of firm quality which is brought up on recent studies (e.g. Novy-Marx, Asness et al.) this risk factor is not able to differentiate average returns but shows increasing importance on regression tests. Thus, quality characteristics seem to play a bigger part in the pricing of firms on the present day when compared to earlier periods.

5.4 Tests on Size and Investment Portfolios

Tests on the size and investment on 5x5 sorted portfolios are evaluated in this subchapter. The structure is similar to the previous chapters. Risk factor patterns in this table are not as clear and strong as seen on BE/ME and operating profitability sorts. Middle rows of investment seem to have the highest average returns on those tables. However, risk factor patterns in the control period (table 12.a) show support to asset growth/investment effect.

5.4.1 Return patterns

Table 12.a Period one: Average daily returns on (SIZE&INV) 01/1989 - 12/1998

	Small Size	2	3	4	Big Size
Low INV	0,049	0,055	0,064	0,066	0,080
2	0,056	0,068	0,066	0,063	0,073
3	0,060	0,057	0,062	0,059	0,067
4	0,052	0,056	0,055	0,058	0,079
High INV	0,022	0,040	0,056	0,062	0,084

Table 12.b Period two: Average daily returns on (SIZE&INV) 01/1999 - 12/2008

	Small Size	2	3	4	Big Size
Low INV	0,048	0,034	0,029	0,030	0,011
2	0,045	0,036	0,037	0,025	0,015
3	0,055	0,050	0,036	0,032	0,014
4	0,044	0,045	0,039	0,043	0,014
High INV	0,007	0,005	0,009	0,014	-0,014

Table 12.c Period three: Average daily returns on (SIZE&INV) 01/2009 - 12/2018

	Small Size	2	3	4	Big Size
Low INV	0,060	0,062	0,063	0,061	0,061
2	0,062	0,060	0,058	0,065	0,046
3	0,063	0,061	0,066	0,066	0,051
4	0,047	0,063	0,060	0,061	0,051
High INV	0,040	0,056	0,056	0,064	0,068

Table twelve presents average daily returns for 25 portfolios sorted by size measured as market capitalization and the investments measured as change in total assets for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis).

Firms on investment rows one and two have higher returns on the first four size columns than firms that are located in higher rows of investment. Biggest size column excludes this effect by having slightly higher returns on the highest investment row than in the lowest investment row. Period one also reveals that investment row three, which stands for average investing firms has the highest or close to the highest returns on all size columns. The size effect reverses in this sort and period as firms in bigger size columns have higher average returns than firms on smaller size columns.

Period two (table 12.b) provides more interesting results on average returns. Investment effect is supported once again with low investing firms having significantly higher returns in all size columns on extreme investment rows. But the pattern of investment effect is not that straightforward. Highest returns in the second period are found from the investment rows three and four. Extremely low investing firms have a bit lower returns than firms on investment rows three and four. Highest investment row provides close to zero returns on all size columns turning negative on the biggest size column. Similar to other sorts, the size effect is once again visible in the second period as smaller the size column higher the return.

Period three (table 12.c) follows to be characteristic with low return dispersion as all size and investment categories seem to perform pretty well. But this period three size and investment sorts, seem to differentiate from book-to-market and operating profitability sorts as investment effects are mildly visible on the first three size columns. Lowest investment row provides a steady return (0.061) on average, which beats the returns of firms on the high investing rows on the first three size columns, slightly losing on bigger size columns. Two lowest investment rows perform well and steadily as seen on the other periods too, but investment row three seems to have the highest returns on the three size columns out of five.

Differences between the (01/1999 - 12/2008) and (01/2009 - 12/2018) are visible in the tables, although tables are closer to each other than in the other sorts when evaluating risk factor return patterns. Biggest size column seems to underperform in the second period compared to control and the last period. On period three, the biggest size column has taken it returns back. Strong returns of the investment row three and lower dispersion of average returns between differently investing firms are visible in the last period suggesting investment effect is not as strong on all market states similar to other risk factors. In period three (table 12.c) investment extreme rows, on three smallest size columns, low investing firms beat the high investing firms, but on the two biggest size columns effect reverses. Differentiation of firms with investment and size categories seem to work on extremes in case of small or medium-sized firms. But this differentiation achieves not too much as average investing (investment row three) firms beat those extremes nearly in every case studied here. Size effect seems to disappear again as we come to period three, finding support only from the second period from size and investment sorted portfolios.

5.4.2 Performance of FF5

Table 13.a Period one: Adjusted R^2 values for regression (SIZE&INV) 01/1989 - 12/1998

	Small Size	2	3	4	Big Size
Low INV	0,866	0,872	0,803	0,816	0,833
2	0,806	0,853	0,827	0,848	0,927
3	0,794	0,841	0,863	0,878	0,925
4	0,838	0,899	0,894	0,885	0,932
High INV	0,905	0,953	0,925	0,882	0,939

Table 13.b Period two: Adjusted R^2 values for regression (SIZE&INV) 01/1999 - 12/2008

	Small Size	2	3	4	Big Size
Low INV	0,905	0,958	0,914	0,901	0,894
2	0,920	0,932	0,911	0,892	0,932
3	0,913	0,950	0,921	0,909	0,925
4	0,930	0,956	0,924	0,895	0,941
High INV	0,908	0,961	0,938	0,918	0,959

Table 13.c Period three: Adjusted R^2 values for regression (SIZE&INV) 01/2009 - 12/2018

	Small Size	2	3	4	Big Size
Low INV	0,953	0,962	0,929	0,928	0,933
2	0,952	0,968	0,952	0,947	0,945
3	0,942	0,964	0,957	0,948	0,962
4	0,947	0,974	0,962	0,944	0,970
High INV	0,953	0,972	0,954	0,929	0,939

Table thirteen presents the adjusted R^2 values of the 25 regressions made to portfolios sorted on size measured as market capitalization and investments measured as change in total assets for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis). For a detailed description of the adjusted R^2 value check the first part of chapter 4. Asset pricing models.

FF5 performance follows similar patterns as seen before in the regressions made to book-to-market and operating profitability sorts. Control period (table 13.a) provides the worst performance with six significant intercepts and average absolute intercept of (0.007). Adjusted R^2 average is (0.872), and dispersion is again large as (0.159) between the lowest and highest R^2 value. Significant intercepts decrease and adjusted R^2 increases, coming to period two (table 13.b). Performance is lower compared to the control period in the absolute intercept category as it rises to (0.009) on period two, despite a high increase in R^2 values which dispersion decreases to (0.068).

On period three (table 13.c), high performance is confirmed in size and investment sorts also. Period three table shows the best performance with (0.005) average absolute intercepts, high adjusted R^2 on (0.951) on average and dispersion of R^2 values only (0.035). What was different from the BE/ME and operating profitability sorts, there were (3) significant intercepts on the period three regressions despite the high explanatory power of the model. Two out of three of those significant intercept values were found from the middle investment row, which was already pointed out on the average returns. Those intercept values were positive, suggesting these firms in the middle investment row seem to have some advantage on average returns compared to other categories of size and investment on this sort.

5.4.3 Factor loadings

Below on tables fourteen, fifteen and sixteen, the regression outcomes from tests on size and investments are reported.

First, starting with joint examination. Evaluating the importance of the CMA (investment factor) starts with absolute average coefficients. It increases from the control period (0.279) with 22 significant coefficients to (0.281) into the second period with 23 significant coefficients. The slightly higher increase is present in the last period as the average absolute coefficient rises to (0.285) with 21 significant coefficients. Suggesting CMA factor has pretty steady explanatory power around periods in its own sort made by size and investments. Movements of CMA factor are not even close as high as the increase in the explanatory power of RMW in the sorts of size and operating profitability or decrease of HML on its own sort. Similar average absolute figures for RMW factor in this sort are following (0.131) with 21 significant coefficients in the period one, sharp rise to (0.170) in period two with 23 significant coefficients and decrease to (0.144) in period three with 20 significant coefficients.

Average factor loadings for the market, HML, and SMB factors provide similar story as before, and movements of these factors seem to be robust trends as those are visible on all three 5x5 sorts. The market drives more returns on period three (table 16) than on the two first periods (table 14, 15) also in the sorts of size and investment. Market factor average coefficient is (0.992) in (table 14) which lowers to (0.987) in (table 15) and rises to (1.002) in (table 16). SMB has also a sharp increase in average absolute coefficients between the second and the third period. SMB average absolute coefficient rises from the second period (0.581) to (0.610) in the third period, which is very close to the control period value of (0.609).

Table 14. Period one: regressions on portfolios formed on size and investments (01/1989 - 12/1998)

$$R_i - R_{ft} = a_i + b_iMKT_t + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size
Low INV	0,003	-0,002	-0,006	-0,003	0,004
2	0,009	0,012	0,007	-0,002	-0,001
3	0,012	0,004	0,003	-0,007	-0,013
4	0,006	0,006	-0,001	-0,003	0,006
High INV	-0,024	-0,010	0,004	0,006	0,017

t(a)	Small Size	2	3	4	Big Size
Low INV	0,576	-0,330	-0,843	-0,389	0,572
2	1,825	2,443	1,383	-0,382	-0,291
3	2,244	0,773	0,625	-1,429	-2,806
4	1,136	1,299	-0,185	-0,616	1,211
High INV	-4,895	-2,406	0,688	0,894	3,243

b	Small Size	2	3	4	Big Size
Low INV	1,004	1,132	1,218	1,059	1,090
2	0,798	0,920	0,900	0,926	0,973
3	0,798	0,874	0,942	0,981	1,028
4	0,854	0,941	1,010	1,011	0,972
High INV	1,019	1,150	1,154	1,111	0,944

t(b)	Small Size	2	3	4	Big Size
Low INV	94,346	102,114	83,141	85,648	80,989
2	80,708	98,402	90,686	94,650	119,207
3	78,074	91,598	99,047	105,315	112,826
4	86,515	108,113	103,913	95,720	107,287
High INV	107,417	143,664	105,705	80,564	92,512

s	Small Size	2	3	4	Big Size
Low INV	0,987	0,963	0,745	0,353	-0,091
2	0,811	0,827	0,571	0,279	-0,243
3	0,799	0,786	0,631	0,293	-0,249
4	0,848	0,866	0,691	0,307	-0,287
High INV	1,012	1,030	0,805	0,444	-0,297

t(s)	Small Size	2	3	4	Big Size
Low INV	66,172	61,949	36,297	20,382	-4,798
2	58,430	63,084	41,011	20,354	-21,255
3	55,744	58,716	47,305	22,453	-19,472
4	61,272	70,975	50,686	20,707	-22,565
High INV	76,123	91,729	52,625	22,964	-20,742

h	Small Size	2	3	4	Big Size
Low INV	-0,050	0,000	0,234	0,301	-0,128
2	0,129	0,188	0,257	0,307	-0,108
3	0,192	0,283	0,332	0,374	0,095
4	0,101	0,170	0,191	0,214	0,019
High INV	-0,036	-0,119	-0,128	-0,086	-0,108

t(h)	Small Size	2	3	4	Big Size
Low INV	-2,325	-0,005	7,902	12,039	-4,718
2	6,457	9,960	12,840	15,539	-6,541
3	9,281	14,690	17,283	19,877	5,160
4	5,053	9,704	9,725	10,029	1,060
High INV	-1,860	-7,374	-5,826	-3,083	-5,255

r	Small Size	2	3	4	Big Size
Low INV	-0,364	-0,196	-0,049	-0,076	-0,190
2	-0,051	0,122	0,040	-0,001	-0,059
3	0,004	0,082	0,070	-0,071	0,167
4	-0,110	-0,061	-0,124	-0,186	0,046
High INV	-0,268	-0,247	-0,313	-0,327	0,061

t(r)	Small Size	2	3	4	Big Size
Low INV	-14,515	-7,524	-1,427	-2,625	-6,013
2	-2,176	5,556	1,713	-0,045	-3,071
3	0,158	3,656	3,113	-3,244	7,798
4	-4,717	-2,959	-5,417	-7,479	2,135
High INV	-11,991	-13,132	-12,188	-10,087	2,535

c	Small Size	2	3	4	Big Size
Low INV	0,296	0,358	0,295	0,229	0,838
2	0,184	0,195	0,131	0,122	0,627
3	0,116	-0,001	-0,081	0,001	0,173
4	0,112	-0,131	-0,229	-0,293	-0,197
High INV	0,013	-0,292	-0,540	-0,612	-0,896

t(c)	Small Size	2	3	4	Big Size
Low INV	12,700	14,778	9,203	8,472	28,459
2	8,494	9,525	6,040	5,685	35,134
3	5,198	-0,058	-3,890	0,048	8,662
4	5,183	-6,876	-10,775	-12,656	-9,956
High INV	0,640	-16,676	-22,625	-20,271	-40,107

Table fourteen contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and investments in control period of (01/1989 – 12/1998). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Investments increase from up to bottom from low investing firms on the first quantile to the high investing firms in the last quantile. Investment level is estimated by percentage change in total assets. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

Table 15. Period two: regressions on portfolios formed on size and investments (01/1999 - 12/2008)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size	t(a)	Small Size	2	3	4	Big Size
Low INV	0,017	-0,001	0,009	0,011	-0,009	Low INV	1,798	-0,207	0,949	1,242	-0,965
2	0,004	-0,005	0,005	-0,001	-0,003	2	0,639	-0,705	0,688	-0,080	-0,409
3	0,013	0,008	0,005	0,009	-0,002	3	1,809	1,264	0,635	1,170	-0,315
4	0,004	0,005	0,014	0,023	0,002	4	0,637	0,825	1,769	2,549	0,278
High INV	-0,022	-0,016	0,007	0,027	0,005	High INV	-2,578	-2,394	0,807	2,538	0,747

b	Small Size	2	3	4	Big Size	t(b)	Small Size	2	3	4	Big Size
Low INV	0,926	1,156	1,044	0,996	1,016	Low INV	113,340	188,861	132,383	128,991	130,874
2	0,836	1,014	0,968	0,979	0,978	2	139,648	160,622	139,038	131,908	171,685
3	0,819	1,037	0,973	0,935	0,959	3	133,558	183,651	152,787	141,954	160,632
4	0,855	1,043	1,016	1,006	1,083	4	147,980	195,928	149,311	128,637	178,218
High INV	0,881	1,058	1,036	1,088	0,980	High INV	119,550	185,679	139,727	116,955	171,028

s	Small Size	2	3	4	Big Size	t(s)	Small Size	2	3	4	Big Size
Low INV	1,005	1,077	0,577	0,183	-0,198	Low INV	64,890	92,835	38,620	12,491	-13,486
2	0,883	0,853	0,587	0,153	-0,142	2	77,799	71,254	44,493	10,889	-13,119
3	0,899	0,989	0,545	0,255	-0,179	3	77,313	92,399	45,132	20,428	-15,782
4	0,916	0,961	0,622	0,328	-0,154	4	83,647	95,322	48,234	22,113	-13,348
High INV	0,927	0,966	0,649	0,354	-0,136	High INV	66,379	89,516	46,181	20,056	-12,488

h	Small Size	2	3	4	Big Size	t(h)	Small Size	2	3	4	Big Size
Low INV	0,067	0,107	0,051	0,248	-0,078	Low INV	4,272	9,171	3,399	16,806	-5,296
2	0,280	0,217	0,244	0,217	-0,077	2	24,467	17,984	18,391	15,344	-7,038
3	0,300	0,188	0,203	0,210	0,038	3	25,642	17,490	16,684	16,700	3,347
4	0,267	0,241	0,053	0,087	0,100	4	24,248	23,769	4,049	5,847	8,648
High INV	0,116	-0,021	-0,092	-0,170	-0,095	High INV	8,251	-1,889	-6,482	-9,579	-8,712

r	Small Size	2	3	4	Big Size	t(r)	Small Size	2	3	4	Big Size
Low INV	-0,397	-0,264	-0,341	-0,317	-0,117	Low INV	-21,948	-19,466	-19,537	-18,533	-6,809
2	0,044	0,132	-0,034	0,028	0,150	2	3,310	9,448	-2,216	1,719	11,917
3	0,129	0,091	0,132	0,020	0,257	3	9,472	7,283	9,358	1,337	19,407
4	0,041	0,167	0,062	0,043	0,260	4	3,236	14,171	4,085	2,509	19,303
High INV	-0,143	-0,190	-0,307	-0,486	-0,106	High INV	-8,786	-15,067	-18,701	-23,576	-8,314

c	Small Size	2	3	4	Big Size	t(c)	Small Size	2	3	4	Big Size
Low INV	0,360	0,341	0,332	0,476	0,998	Low INV	16,218	20,480	15,510	22,710	47,335
2	0,158	0,206	0,238	0,415	0,553	2	9,728	11,997	12,606	20,597	35,738
3	0,082	0,175	0,133	0,211	0,255	3	4,949	11,405	7,701	11,797	15,690
4	0,084	-0,022	0,008	0,081	0,046	4	5,362	-1,533	0,416	3,800	2,796
High INV	-0,045	-0,195	-0,417	-0,445	-0,737	High INV	-2,244	-12,597	-20,695	-17,608	-47,303

Table fifteen contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and investments in period two of (01/1999 – 12/2008). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Investments increase from up to bottom from low investing firms on the first quantile to the high investing firms in the last quantile. Investment level is estimated by percentage change in total assets. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

Table 16. Period three: regressions on portfolios formed on size and investments (01/2009 - 12/2018)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

a	Small Size	2	3	4	Big Size
Low INV	0,004	-0,004	0,000	-0,001	0,006
2	0,011	0,002	-0,001	0,005	-0,008
3	0,013	0,003	0,012	0,011	-0,002
4	-0,003	0,005	0,001	0,003	-0,004
High INV	-0,012	-0,003	-0,004	0,002	0,010

t(a)	Small Size	2	3	4	Big Size
Low INV	0,561	-0,646	-0,020	-0,163	1,031
2	1,793	0,377	-0,258	0,982	-1,760
3	1,932	0,571	2,298	2,126	-0,441
4	-0,555	1,190	0,222	0,531	-1,161
High INV	-1,986	-0,642	-0,612	0,287	1,693

b	Small Size	2	3	4	Big Size
Low INV	0,967	1,140	1,105	1,104	1,005
2	0,890	1,007	1,030	1,045	0,958
3	0,866	0,997	0,958	0,977	0,946
4	0,869	1,000	1,026	1,027	0,998
High INV	0,912	1,025	1,043	1,096	1,049

t(b)	Small Size	2	3	4	Big Size
Low INV	128,656	158,240	125,726	135,110	152,610
2	128,925	173,342	156,958	162,890	176,832
3	114,598	164,393	164,671	166,109	209,788
4	121,843	193,432	176,756	158,239	232,751
High INV	127,595	180,667	154,774	133,183	155,503

s	Small Size	2	3	4	Big Size
Low INV	1,104	1,017	0,599	0,260	-0,144
2	1,044	0,944	0,593	0,243	-0,177
3	1,055	0,942	0,561	0,214	-0,149
4	1,038	0,939	0,607	0,273	-0,158
High INV	1,062	0,964	0,671	0,338	-0,152

t(s)	Small Size	2	3	4	Big Size
Low INV	84,152	80,895	39,065	18,218	-12,524
2	86,655	93,022	51,778	21,673	-18,670
3	79,945	88,977	55,254	20,869	-18,929
4	83,345	104,039	59,918	24,080	-21,104
High INV	85,129	97,343	57,014	23,548	-12,907

h	Small Size	2	3	4	Big Size
Low INV	-0,018	0,023	0,019	0,019	-0,024
2	0,195	0,154	0,077	0,033	-0,077
3	0,262	0,153	0,162	0,060	0,039
4	0,255	0,202	0,048	-0,014	0,064
High INV	-0,056	-0,136	-0,102	-0,111	-0,159

t(h)	Small Size	2	3	4	Big Size
Low INV	-1,383	1,830	1,264	1,357	-2,149
2	16,398	15,443	6,838	2,968	-8,283
3	20,139	14,629	16,198	5,956	4,970
4	20,770	22,675	4,765	-1,277	8,673
High INV	-4,531	-13,911	-8,777	-7,820	-13,655

r	Small Size	2	3	4	Big Size
Low INV	-0,467	-0,290	-0,195	-0,156	-0,133
2	-0,035	0,054	0,022	0,041	-0,008
3	0,003	0,115	0,132	0,095	0,096
4	0,017	0,136	0,084	0,065	0,100
High INV	-0,471	-0,341	-0,211	-0,204	-0,130

t(r)	Small Size	2	3	4	Big Size
Low INV	-21,565	-13,988	-7,710	-6,640	-7,001
2	-1,769	3,242	1,165	2,215	-0,502
3	0,132	6,563	7,874	5,610	7,426
4	0,846	9,130	5,050	3,480	8,096
High INV	-22,908	-20,859	-10,895	-8,599	-6,712

c	Small Size	2	3	4	Big Size
Low INV	0,328	0,452	0,496	0,517	0,685
2	0,108	0,162	0,292	0,267	0,557
3	-0,061	0,061	0,047	0,160	0,139
4	-0,214	-0,170	-0,064	-0,029	-0,189
High INV	-0,327	-0,400	-0,338	-0,319	-0,735

t(c)	Small Size	2	3	4	Big Size
Low INV	13,502	19,385	17,458	19,574	32,162
2	4,830	8,614	13,735	12,847	31,792
3	-2,489	3,115	2,504	8,415	9,498
4	-9,292	-10,188	-3,400	-1,390	-13,656
High INV	-14,165	-21,801	-15,490	-11,997	-33,708

Table sixteen contains regression outcomes from 25 regression on 5x5 sorted portfolios by size and investments in period three of (01/2009 – 12/2018). Size variable increases from the left to right from small firms to big firms, size measured as market capitalization. Investments increase from up to bottom from low investing firms on the first quantile to the high investing firms in the last quantile. Investment level is estimated by percentage change in total assets. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on simple t-test.

HML factor plays a similar part as on other sorts. The decreasing trend of HML explanation power is also observed on these sorts of size and investment. On these sorts, HML has slight decrease from period one (0.166) with 22 significant coefficients to period two (0.151) with 24 significant coefficients. The decrease is very sharp of thirty-five percentages between second and the third period as average absolute coefficient lowers to (0.098) with 21 significant coefficients.

Second, evaluating single coefficients and extremes. Sorts provide CMA loadings as expected. Firms in low investment rows have high significant coefficients that increase as size increases and firms on high investment rows provide similar negative coefficients. The only expectation is the firms on high investment rows on the smallest size columns on the first two periods (table 14, 15) as those firms seem to take very close to zero loadings to CMA factor. This expectation disappears coming to last period (table 16) as coefficient decreases from (-0.045) to (-0.327). Variation is seen between the second and third period, but none major changes are visible except for the smallest size column. Its CMA coefficients turn from positive or near-zero loadings to highly negative on period three. CMA seems to provide the same and steady coefficients to both extreme investment rows on absolute average terms of (0.45) what is different from other sorts. Thus, CMA factor is as good in explain returns of high and low investing firms at least in the extreme categories of investment.

RMW coefficients seem to provide us with some explanation why the firms on middle rows of investment outperform investment extremes on the average return tables investigated before. Middle investment row firms seem to have positive coefficients on profitability factor as investment extremes have highly negative coefficients of both rows of low and high investments. This suggests that main results found in the average returns of size and investment sorts are not too much explained with differences in levels of investments, moreover those differences are explained with differences in operating profitability. As good performance in average returns on middle rows of investment on control period (table 12.a) was weaker than in the last two periods, the RMW coefficients are also lower in the middle rows at the control period, finding more support to statement.

5.4.4 Highlights on size and investments tests

Return patterns in those sorts were interesting. Differences between extremely low and high investing firms were visible in all three periods. But not further support was given to investment/asset growth effect in general as middle investment rows that seem to be more profitable on average (based on RMW coefficients) were able to beat returns of extreme categories. RMW, profitability factor loadings were visible on all three periods, which suggest that this is the difference that mainly drives the results on average returns on size and investment sorts. Middle investment rows having positive coefficients and extreme categories of investment having negative coefficients on profitability. This finding suggests that main results found in the average returns of size and investment sorts are not too much explained with differences in levels of investments, moreover those differences are explained with differences in operating profitability. Performance statics followed the similar story as before confirming the robust best performance of FF5 on period three.

CMA risk factor has pretty steady explanatory power around the different periods in its own sort. CMA seems to be as good explaining the returns on high and low investing firms and different from other factors it can generate similar explanatory power in both directions of extreme. Average coefficients for market factor, HML, and SMB factors provide similar story as before, and movements of these factors seem to be robust trends as those are visible on all three 5x5 sorts.

As investments or operating profitability could not provide very strong patterns in period three, quality characteristics could be better in the differentiating firms in this period three than the other risk factors. This is supported as middle row firms seem to have positive coefficients on profitability and extremes having negative coefficients. Size effect was only visible on the second period (table 12.b), which follows the same results as seen in BE/ME and operating profitability tests.

5.5 Tests on Size, Operating Profitability and Investment Portfolios

Below in (table 17) is reported the average monthly returns for Fama-French five factors and the risk-free rate at the same period. This subchapter follows the same structure as the previous analysis chapters, but we focus now on the monthly values and their relative changes on portfolios sorted on 2x4x4. Meaning that there are two size categories, small and big firms and four categories of operating profitability and investments. These sorts result in thirty-two different portfolios.

Table 17.a Average monthly returns on Fama-French five factors and the risk-free rate on time period of (01/1989 – 12/1998)

	$M_R - R_f$	SMB	HML	RMW	CMA	R_f
Average	1,056	-0,330	0,189	0,395	0,123	0,431
Stand. Dev.	3,918	2,637	2,317	1,388	1,786	0,138
Median	1,305	-0,410	0,110	0,445	-0,005	0,420

Table 17.b Average monthly returns on Fama-French five factors and the risk-free rate on time period of (01/1999 – 12/2008)

	$M_R - R_f$	SMB	HML	RMW	CMA	R_f
Average	-0,217	0,604	0,437	0,516	0,501	0,264
Stand. Dev.	4,542	3,736	3,642	3,940	2,669	0,146
Median	0,700	0,290	0,100	0,520	0,140	0,275

Table 17.c Average monthly returns on Fama-French five factors and the risk-free rate on time period of (01/2009 – 12/2018)

	$M_R - R_f$	SMB	HML	RMW	CMA	R_f
Average	1,106	0,071	-0,163	0,107	0,024	0,026
Stand. Dev.	4,041	2,480	2,657	1,542	1,465	0,047
Median	1,325	0,165	-0,275	0,120	-0,020	0,010

Table seventeen presents average monthly returns, median monthly returns, and standard deviation of return for Fama-French risk-factors and the risk-free rate for three time periods evaluated in this thesis. For detailed description of factors check chapter 5.1.2 Variable construction.

Average returns on the factors are discussed on a daily basis at chapter 5.1.3 and not repeated here. Most important changes between the periods are in the low average of the risk-free rate in period three (table 17.c) that definitely has an effect on the equity market and actions of its participants.

5.5.1 Return patterns

Sorts of thirty-two portfolios provide more information about the operating profitability and investments effects not focusing too much on size, which should help in giving additional information to the analysis. The analysis focuses on extremes and their averages, giving a new approach to the evaluation of return patterns. A new approach should be beneficial as extremes on operating profitability and investment are larger in 2x4x4 sorts as firms are sorted in four categories instead of five.

Table 18.a Period one: Average monthly returns on (SIZE&OP&INV) 01/1989 - 12/1998

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	0,955	1,493	1,619	1,640	1,754	1,536	1,488	1,778
2	1,293	1,219	1,465	1,478	1,108	1,338	1,521	1,572
3	0,580	1,328	1,367	1,441	1,658	1,307	1,445	1,861
High INV	0,174	1,043	1,254	1,205	1,268	1,354	1,579	1,902

Table 18.b Period two: Average monthly returns on (SIZE&OP&INV) 01/1999 - 12/2008

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	0,680	0,933	1,065	0,913	0,189	0,605	0,334	0,139
2	0,974	0,984	0,624	0,638	-0,290	0,355	0,629	0,271
3	0,496	1,047	0,941	1,030	0,327	0,156	0,259	0,180
High INV	-0,307	0,527	0,737	0,811	-0,510	-0,276	-0,066	0,188

Table 18.c Period three: Average monthly returns on (SIZE&OP&INV) 01/2009 - 12/2018

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	1,131	1,245	1,237	1,460	0,880	1,050	1,313	1,313
2	1,302	1,168	1,177	1,293	1,087	1,191	1,111	1,112
3	1,261	1,241	1,120	1,165	1,046	1,179	0,944	0,785
High INV	0,884	1,038	1,282	1,074	1,220	1,249	1,467	1,421

Table eighteen presents average monthly returns for 32 portfolios sorted by size measured as market capitalization, operating profitability and the investments measured as change in total assets for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis).

In these sorts, the investment effect is not so visible as the effect can be seen only on two out of six sets of sixteen portfolios. On the period one (table 18.a) using the whole investing rows on extremes (low and high levels of investment) of each operating profitability columns, the high investing firms beat low investing firms in small firms' category. This fact is the same for period two (table 18.b) and period three (table 18.c). Support to investment effect is given by big firms in periods one and two, as on these portfolio sets the low investing firms beat high investing firms on average. But this effect disappears again in period three as high investing firms beat low investing firms on average. Thus, support to investment effect in average returns is limited also in those tests of the three variate sorts.

Operating profitability and effect of higher average returns of high operating profitability firms is strongly supported in these sorts. In every period and average returns of extreme operating profitability columns (comparing low OP and high OP columns), high operating profitability firms beat the low operating profitability firms. The difference in average returns between low operating profitability and high operating profitability firms is much lower in period three, but still visible and supported.

Evaluating size effect takes now a broader view only dividing firms into two quantiles based on the NYSE market capital breakpoints. As expected by hints on 5x5 sorts in the period one (table 18.a), big firms beat the small firms and small firms beat big firms on the period two (table 18.b) on average returns like seen on other sorts. An expectation to earlier findings is that in the period three (table 18.c) the small firms beat big firms in all extreme categories excluding the high investment category as big high investing firms beat small high investing firms. On other categories, small firms have higher returns on low investing rows, low operating profitability columns and high operating profitability columns. Thus, in the period three size effect is visible on three out of four comparisons of risk factor extremes. Another important pick is the very low average returns on the big size category in period two and lower returns of small firms in the same period. On the period three returns are less dispersed as seen on all sorts, but these sorts still provide some patterns in returns when using these three characteristics to differentiate firms.

5.5.2 Performance of FF5

Evaluating the performance of the FF5 model in the three-variate sort portfolios reveals additional information to the analysis. It needs to be noticed, that these regressions are made with twenty times fewer observations than regressions in the 5x5 sorts with daily data which most surely has an effect on the FF5 performance. Although main differences found in the 2x4x4 sorts is the much weaker performance of FF5 model in explaining the big size firms than the small-sized firms. This is very much the opposite than the findings in the previous studies that used the monthly data. On previous studies, FF5 had difficulties in explaining excess returns of small firms, not the big firms.

On three-variate sorts, period two FF5 model performance (table 19.b) lowers near to the control period (table 19.a) in explaining excess returns.

Table 19.a Period one: Adj. R^2 values for regressions (SIZE&OP&INV) 01/1989 - 12/1998

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	0,933	0,863	0,821	0,886	0,847	0,730	0,797	0,853
2	0,895	0,900	0,902	0,920	0,848	0,795	0,850	0,859
3	0,901	0,915	0,942	0,933	0,887	0,803	0,888	0,896
High INV	0,936	0,937	0,960	0,973	0,876	0,849	0,871	0,872

Table 19.b Period two: Adj. R^2 values for regressions (SIZE&OP&INV) 01/1999 - 12/2008

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	0,969	0,899	0,838	0,825	0,842	0,800	0,735	0,744
2	0,941	0,917	0,878	0,881	0,714	0,790	0,806	0,713
3	0,940	0,913	0,919	0,914	0,814	0,784	0,676	0,626
High INV	0,964	0,921	0,930	0,934	0,916	0,838	0,793	0,830

Table 19.c Period three: Adj. R^2 values for regressions (SIZE&OP&INV) 01/2009 - 12/2018

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	0,924	0,931	0,880	0,911	0,902	0,870	0,865	0,901
2	0,926	0,944	0,945	0,949	0,854	0,866	0,892	0,877
3	0,914	0,958	0,952	0,948	0,893	0,849	0,908	0,872
High INV	0,932	0,942	0,959	0,948	0,901	0,855	0,875	0,830

Table nineteen presents the adjusted R^2 values of the 32 regressions made to portfolios sorted on size measured as market capitalization, operating profitability and investments measured as change in total assets for three different 120-month time periods. Table a presenting the returns on the control/first period, table b presenting returns on the period two (before the financial crisis breakpoint) and table c presenting results on the period three (after the financial crisis). For a detailed description of the adjusted R^2 value check the first part of chapter 4. Asset pricing models.

The period one has six significant intercepts, average adjusted R^2 of (0.879) and dispersion between the lowest and highest value of R^2 at (0.243). FF5 performs extremely well with R^2 of (0.973) in the category of small firms with on high investments and high operating profitability, which are targeted on these sorts. In period two (table 19.b), the R^2 dispersion increases to (0.342) and average adjusted R^2 decreases to (0.844). There are two significant intercept values with the average absolute intercept value of (0.169). However, a dramatic increase in R^2 dispersion and much lower performance explaining the returns of big sized firms (average R^2 on big firms is only 0.776) questions the performance of FF5 in explaining the average excess returns with low-frequency data at shorter periods.

Once again, period three (table 19.c) provides the significantly highest performance of the model. Average absolute intercept is (0.123) in a month, with two significant values. Adjusted R^2 increases to (0.905) on average. A most significant change between the second and the third period is much lower R^2 dispersion, which is only (0.13). FF5 is pretty steady at explaining the returns of firms with different characteristics in the last period. Main findings of these three-variate sorts are significantly lower performance of FF5 in explaining low-frequency returns of big firms compared to small firms.

5.5.3 Factor loadings

Below on tables twenty to twenty-five the regression outcomes are reported. As discussed before in performance evaluation, because there is much less data, these outcomes have much less significant coefficients which make it much more difficult to compare those periods in terms of single coefficients or using joint examination. Results on these tests should be only seen as supportive to analysis on 5x5 portfolios. In 2x4x4 sorts RMW seems to play important part in explanation of returns. High and low operating profitability columns seem provide significant results as most of the RMW coefficients are statistically significant in both small and big size categories. CMA has weak performance in case of significant coefficients in smaller size category, however, on big firms' category, there is much more significant CMA coefficients despite the average low performance of FF5 model. In small firms' category all market excess return and SMB coefficients are again significant. There are nineteen significant HML coefficients on the second period (table 21) and on the period three (table 22). On the first period (table 20) HML has only seven significant coefficients. On big firm's category importance of SMB and HML factors decrease significantly.

Using joint examination as the evaluation of absolute average slopes on these three periods reveals that market explanatory power on returns has varied a bit differently than in daily data. On small firms, average MKT coefficients have been (1.001), (1,030), (1,008). And a similar trend is seen on the big firms (0.996), (1,038), (1,005). Market captures most variation in the second period which is direct opposite from the daily tests as market had the lowest average coefficient on second period. But as the daily data has twenty times more observations conclusions can be made that MKT factor captures variation that is left unexplained by other factors in low frequently data seeing this result as not that important one as trend is similar in all daily sorts.

Table 20. Period one: Small firms, regression on portfolios formed on size, operating profitability and investments (01/1989 – 12/1998)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

SMALL SIZED FIRMS:

a					t(a)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,061	0,138	0,245	0,201	Low INV	-0,385	0,750	1,286	1,188
2	0,217	-0,037	0,265	0,045	2	1,182	-0,298	2,271	0,359
3	-0,563	0,134	0,169	0,145	3	-3,277	1,006	1,692	1,242
High INV	-0,548	0,004	0,035	-0,062	High INV	-3,039	0,028	0,299	-0,626

b					t(b)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	1,137	1,054	0,945	1,104	Low INV	24,224	19,458	16,854	22,224
2	1,048	0,881	0,805	0,958	2	19,412	23,849	23,474	26,050
3	1,072	0,949	0,868	0,917	3	21,228	24,242	29,604	26,683
High INV	1,117	1,022	1,065	1,081	High INV	21,081	23,733	30,954	37,012

s					t(s)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	1,205	0,985	0,872	1,001	Low INV	19,775	14,005	11,973	15,509
2	0,990	0,668	0,671	0,837	2	14,123	13,924	15,077	17,510
3	0,887	0,737	0,709	0,760	3	13,527	14,510	18,604	17,026
High INV	0,949	0,956	0,958	1,055	High INV	13,785	17,092	21,443	27,828

h					t(h)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,243	0,191	0,094	0,089	Low INV	-2,602	1,765	0,844	0,902
2	0,200	0,248	0,315	0,390	2	1,857	3,362	4,614	5,321
3	-0,069	0,122	0,292	0,336	3	-0,683	1,558	5,002	4,907
High INV	-0,603	-0,154	0,081	0,071	High INV	-5,708	-1,789	1,176	1,217

r					t(r)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,615	0,084	0,402	0,170	Low INV	-5,353	0,634	2,928	1,397
2	-0,438	0,109	0,180	0,467	2	-3,317	1,209	2,144	5,182
3	-0,387	-0,081	0,088	0,277	3	-3,126	-0,848	1,224	3,296
High INV	-1,148	-0,282	0,036	0,195	High INV	-8,844	-2,672	0,432	2,721

c					t(c)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	0,581	0,544	0,458	0,717	Low INV	3,991	3,236	2,634	4,649
2	0,006	0,205	0,087	0,064	2	0,037	1,791	0,815	0,562
3	0,306	0,116	-0,049	-0,211	3	1,951	0,953	-0,541	-1,975
High INV	-0,072	-0,126	-0,405	-0,384	High INV	-0,439	-0,945	-3,795	-4,235

Table twenty contains regression outcomes from 16 regressions on 2x4x4 sorted portfolios by size, operating profitability, and investments in control period of (01/1989 – 12/1998). Size variable is steady around table and reported at left upper corner, firms are divided to small and big firms using NYSE breakpoint for market capitalization. Investment level increases from top of the table to bottom, from low investing firms on the first quantile to the high investing firms in the last quantile. The operating profitability level increases from left to right. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on t-test.

Table 21. Period one: Big firms, regression on portfolios formed on size, operating profitability and investments (01/1989 – 12/1998)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

BIG SIZED FIRMS:

		a					t(a)		
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,577	0,255	-0,129	0,007	Low INV	3,242	1,388	-0,747	0,041
2	-0,124	-0,031	-0,233	-0,313	2	-0,804	-0,195	-1,334	-1,914
3	0,274	-0,179	-0,287	0,262	3	1,774	-0,893	-1,974	1,798
High INV	-0,014	-0,111	-0,154	0,671	High INV	-0,074	-0,539	-0,796	3,457

		b					t(b)		
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,985	0,827	0,985	1,061	Low INV	18,803	15,311	19,464	22,656
2	0,904	0,831	1,088	1,081	2	19,958	17,614	21,149	22,443
3	1,015	0,989	1,074	1,008	3	22,388	16,774	25,133	23,513
High INV	1,061	1,042	1,137	0,852	High INV	18,884	17,266	19,962	14,918

		s					t(s)		
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,118	-0,176	-0,128	0,032	Low INV	-1,735	-2,503	-1,952	0,533
2	0,044	-0,207	-0,372	-0,022	2	0,755	-3,383	-5,565	-0,348
3	-0,259	-0,185	-0,085	-0,179	3	-4,399	-2,420	-1,526	-3,213
High INV	0,073	0,148	0,101	-0,255	High INV	1,001	1,887	1,367	-3,443

		h					t(h)		
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,074	0,038	-0,135	-0,033	Low INV	-0,705	0,353	-1,336	-0,357
2	0,379	0,132	0,116	-0,208	2	4,191	1,399	1,131	-2,169
3	0,271	0,297	0,066	-0,219	3	2,999	2,525	0,777	-2,560
High INV	0,024	0,156	0,263	-0,158	High INV	0,215	1,294	2,319	-1,390

		r					t(r)		
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,847	-0,353	0,090	0,445	Low INV	-6,603	-2,666	0,727	3,882
2	-0,518	-0,122	0,017	0,694	2	-4,668	-1,058	0,135	5,882
3	-0,552	-0,190	0,259	0,199	3	-4,971	-1,317	2,474	1,893
High INV	-0,473	0,057	0,375	-0,068	High INV	-3,437	0,387	2,684	-0,488

		c					t(c)		
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,127	0,416	0,759	0,501	Low INV	0,781	2,483	4,832	3,447
2	-0,053	0,128	0,192	0,587	2	-0,375	0,874	1,204	3,923
3	-0,302	-0,256	0,197	0,066	3	-2,146	-1,400	1,481	0,499
High INV	-0,508	-0,569	-0,510	-1,027	High INV	-2,916	-3,036	-2,881	-5,796

Table twenty-one contains regression outcomes from 16 regressions on 2x4x4 sorted portfolios by size, operating profitability, and investments in control period of (01/1989 – 12/1998). Size variable is steady around table and reported at left upper corner, firms are divided to small and big firms using NYSE breakpoint for market capitalization. Investment level increases from top of the table to bottom, from low investing firms on the first quantile to the high investing firms in the last quantile. The operating profitability level increases from left to right. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on t-test.

Table 22. Period two: Small firms, regression on portfolios formed on size, operating profitability and investments (01/1999 – 12/2008)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

SMALL SIZED FIRMS:

a					t(a)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	0,227	-0,004	0,072	0,007	Low INV	1,376	-0,021	0,337	0,032
2	0,397	0,100	-0,240	-0,315	2	2,299	0,734	-1,627	-1,987
3	-0,062	0,198	0,075	0,163	3	-0,340	1,246	0,599	1,197
High INV	-0,203	-0,116	-0,005	0,030	High INV	-1,092	-0,679	-0,035	0,199

b					t(b)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	1,150	1,117	1,024	1,013	Low INV	24,498	22,879	16,929	17,389
2	0,945	1,018	0,846	1,004	2	19,198	26,270	20,097	22,206
3	1,099	0,847	0,905	1,008	3	21,229	18,726	25,229	26,026
High INV	1,059	1,126	1,075	1,246	High INV	19,951	23,051	24,496	28,864

s					t(s)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	1,065	0,785	0,840	0,684	Low INV	20,889	14,818	12,800	10,817
2	0,923	0,681	0,678	0,742	2	17,270	16,209	14,842	15,135
3	0,960	0,993	0,751	0,792	3	17,099	20,219	19,289	18,838
High INV	0,936	0,853	0,942	0,944	High INV	16,251	16,090	19,770	20,150

h					t(h)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,207	0,214	0,380	0,463	Low INV	-2,868	2,849	4,091	5,173
2	0,006	0,407	0,378	0,419	2	0,084	6,842	5,842	6,030
3	-0,019	0,161	0,303	0,336	3	-0,236	2,313	5,498	5,650
High INV	-0,085	0,121	0,234	0,132	High INV	-1,043	1,614	3,461	1,990

r					t(r)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,756	0,224	0,252	0,287	Low INV	-10,433	2,977	2,702	3,197
2	-0,472	0,239	0,217	0,444	2	-6,214	3,994	3,344	6,373
3	-0,317	0,093	0,263	0,481	3	-3,971	1,338	4,751	8,054
High INV	-0,876	0,122	0,199	0,610	High INV	-10,704	1,619	2,944	9,169

c					t(c)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	0,550	0,463	0,295	0,196	Low INV	6,559	5,311	2,726	1,884
2	0,402	0,255	0,195	0,091	2	4,565	3,688	2,587	1,131
3	0,247	0,101	0,151	-0,104	3	2,668	1,245	2,363	-1,501
High INV	-0,428	-0,015	-0,124	-0,312	High INV	-4,514	-0,169	-1,578	-4,046

Table twenty-two contains regression outcomes from 16 regressions on 2x4x4 sorted portfolios by size, operating profitability, and investments in period two of (01/1999 – 12/2008). Size variable is steady around table and reported at left upper corner, firms are divided to small and big firms using NYSE breakpoint for market capitalization. Investment level increases from top of the table to bottom, from low investing firms on the first quantile to the high investing firms in the last quantile. The operating profitability level increases from left to right. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on t-test.

Table 23. Period two: Big firms, regression on portfolios formed on size, operating profitability and investments (01/1999 – 12/2008)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

BIG SIZED FIRMS:

	a					t(a)			
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,239	0,167	-0,087	-0,314	Low INV	1,025	0,851	-0,354	-1,505
2	-0,566	0,145	0,239	0,011	2	-1,850	0,757	1,332	0,057
3	0,393	0,066	0,102	0,038	3	1,630	0,268	0,390	0,158
High INV	0,127	-0,095	0,231	0,366	High INV	0,597	-0,419	0,914	1,392

	b					t(b)			
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	1,165	1,064	1,111	1,028	Low INV	17,567	19,057	15,774	17,302
2	1,164	0,829	1,012	0,833	2	13,348	15,165	19,815	15,326
3	1,146	1,151	0,936	0,834	3	16,660	16,413	12,610	12,236
High INV	0,992	1,169	0,971	1,197	High INV	16,310	18,155	13,467	15,979

	s					t(s)			
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,250	-0,110	-0,122	-0,067	Low INV	-3,469	-1,820	-1,591	-1,045
2	0,154	0,010	0,077	-0,157	2	1,630	0,176	1,395	-2,660
3	-0,271	-0,141	-0,063	-0,275	3	-3,628	-1,857	-0,780	-3,717
High INV	-0,058	-0,239	-0,127	0,060	High INV	-0,885	-3,425	-1,628	0,742

	h					t(h)			
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,090	0,011	0,308	-0,059	Low INV	0,885	0,131	2,841	-0,644
2	0,146	0,273	-0,016	0,023	2	1,087	3,251	-0,205	0,278
3	0,211	0,318	0,322	-0,112	3	1,992	2,948	2,819	-1,067
High INV	0,114	0,136	0,003	-0,402	High INV	1,215	1,370	0,026	-3,492

	r					t(r)			
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,400	0,160	0,219	0,367	Low INV	-3,912	1,855	2,015	4,007
2	0,024	-0,222	0,324	0,248	2	0,179	-2,632	4,113	2,959
3	-0,260	-0,002	0,090	0,240	3	-2,447	-0,017	0,785	2,284
High INV	-0,733	0,024	0,055	0,402	High INV	-7,816	0,246	0,496	3,482

	c					t(c)			
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,513	0,767	0,447	0,575	Low INV	4,329	7,686	3,549	5,420
2	0,190	0,228	0,277	0,265	2	1,220	2,335	3,037	2,727
3	0,247	0,045	-0,106	0,299	3	2,011	0,358	-0,798	2,455
High INV	-0,643	-0,239	-0,605	-0,501	High INV	-5,918	-2,077	-4,694	-3,741

Table twenty-three contains regression outcomes from 16 regressions on 2x4x4 sorted portfolios by size, operating profitability, and investments in period two of (01/1999 – 12/2008). Size variable is steady around table and reported at left upper corner, firms are divided to small and big firms using NYSE breakpoint for market capitalization. Investment level increases from top of the table to bottom, from low investing firms on the first quantile to the high investing firms in the last quantile. The operating profitability level increases from left to right. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on t-test.

Table 24. Period three: Small firms, regression on portfolios formed on size, operating profitability and investments (01/2009 – 12/2018)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

SMALL SIZED FIRMS:

a					t(a)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,164	0,123	-0,122	0,157	Low INV	-0,871	0,767	-0,580	0,877
2	0,064	0,092	0,028	0,013	2	0,396	0,735	0,231	0,103
3	0,151	0,170	0,081	-0,106	3	0,930	1,618	0,732	-0,885
High INV	-0,349	0,009	0,124	-0,174	High INV	-2,037	0,073	1,114	-1,392

b					t(b)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	1,133	1,017	1,103	1,069	Low INV	22,071	23,183	19,182	21,941
2	1,054	0,933	0,960	1,080	2	23,822	27,492	29,217	30,932
3	0,955	0,928	0,874	1,013	3	21,610	32,437	28,924	31,199
High INV	1,086	0,897	0,988	1,034	High INV	23,297	26,591	32,554	30,440

s					t(s)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	1,072	0,867	0,930	1,026	Low INV	12,941	12,249	10,024	13,053
2	0,896	0,799	0,824	0,884	2	12,549	14,590	15,547	15,691
3	0,906	0,799	0,920	0,933	3	12,705	17,321	18,871	17,796
High INV	0,977	0,858	0,990	0,961	High INV	12,987	15,763	20,235	17,531

h					t(h)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,059	0,353	-0,116	0,153	Low INV	-0,645	4,498	-1,131	1,755
2	-0,327	0,318	0,154	0,262	2	-4,131	5,239	2,618	4,196
3	-0,071	0,184	0,343	0,083	3	-0,900	3,604	6,342	1,436
High INV	-0,508	0,159	0,233	0,189	High INV	-6,087	2,632	4,290	3,111

r					t(r)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	-0,750	-0,349	0,053	0,352	Low INV	-5,776	-3,152	0,364	2,859
2	-0,763	0,107	0,213	0,373	2	-6,818	1,250	2,572	4,230
3	-0,444	-0,062	0,379	0,620	3	-3,974	-0,861	4,964	7,553
High INV	-1,256	-0,159	0,158	0,459	High INV	-10,661	-1,868	2,059	5,349

c					t(c)				
SMALL	Low OP	2	3	High OP	**SMALL**	Low OP	2	3	High OP
Low INV	0,404	0,187	0,922	0,360	Low INV	2,594	1,404	5,286	2,434
2	0,391	0,097	0,225	-0,013	2	2,912	0,946	2,258	-0,125
3	-0,057	-0,047	-0,152	0,169	3	-0,427	-0,537	-1,655	1,715
High INV	-0,531	-0,288	-0,402	-0,396	High INV	-3,756	-2,815	-4,368	-3,846

Table twenty-four contains regression outcomes from 16 regressions on 2x4x4 sorted portfolios by size, operating profitability, and investments in period three of (01/2008 – 12/2018). Size variable is steady around table and reported at left upper corner, firms are divided to small and big firms using NYSE breakpoint for market capitalization. Investment level increases from top of the table to bottom, from low investing firms on the first quantile to the high investing firms in the last quantile. The operating profitability level increases from left to right. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on t-test.

Table 25. Period three: Big firms, regression on portfolios formed on size, operating profitability and investments (01/2009 – 12/2018)

$$R_i - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

BIG SIZED FIRMS:

a					t(a)				
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,266	-0,039	0,191	0,182	Low INV	-1,762	-0,247	1,330	1,582
2	0,001	-0,035	0,061	-0,027	2	0,006	-0,209	0,490	-0,210
3	-0,044	0,086	-0,080	-0,318	3	-0,273	0,487	-0,728	-2,359
High INV	0,187	0,111	0,273	0,095	High INV	1,391	0,649	1,668	0,490

b					t(b)				
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	1,049	0,974	0,953	0,955	Low INV	25,486	22,881	24,377	30,503
2	1,070	1,062	0,938	0,940	2	19,171	23,552	27,596	26,843
3	1,036	1,015	0,903	0,943	3	23,770	21,028	30,320	25,667
High INV	0,970	1,048	1,090	1,129	High INV	26,428	22,473	24,441	21,450

s					t(s)				
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,010	-0,097	-0,166	-0,103	Low INV	0,150	-1,413	-2,630	-2,030
2	0,042	0,033	-0,189	-0,036	2	0,470	0,452	-3,455	-0,632
3	-0,003	-0,036	-0,151	-0,031	3	-0,044	-0,463	-3,150	-0,516
High INV	-0,105	-0,164	-0,083	-0,040	High INV	-1,772	-2,175	-1,155	-0,470

h					t(h)				
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,043	0,128	-0,099	-0,160	Low INV	0,580	1,679	-1,421	-2,849
2	0,382	-0,026	-0,062	-0,099	2	3,823	-0,323	-1,022	-1,580
3	0,290	0,349	0,023	-0,087	3	3,714	4,037	0,424	-1,315
High INV	-0,127	-0,061	0,046	-0,085	High INV	-1,942	-0,727	0,571	-0,901

r					t(r)				
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	-0,454	-0,020	0,182	0,220	Low INV	-4,368	-0,181	1,845	2,776
2	-0,535	0,084	-0,164	0,503	2	-3,791	0,739	-1,908	5,684
3	-0,362	0,134	0,081	0,192	3	-3,288	1,097	1,077	2,067
High INV	-0,651	-0,290	-0,087	0,564	High INV	-7,025	-2,463	-0,769	4,240

c					t(c)				
BIG	Low OP	2	3	High OP	**BIG**	Low OP	2	3	High OP
Low INV	0,584	0,614	0,798	0,290	Low INV	4,673	4,754	6,731	3,057
2	-0,321	0,397	0,309	0,282	2	-1,898	2,900	2,996	2,656
3	0,117	-0,498	0,190	0,054	3	0,883	-3,398	2,103	0,483
High INV	-0,394	-0,615	-0,668	-0,802	High INV	-3,538	-4,347	-4,934	-5,022

Table twenty-five contains regression outcomes from 16 regressions on 2x4x4 sorted portfolios by size, operating profitability, and investments in period three of (01/2008 – 12/2018). Size variable is steady around table and reported at left upper corner, firms are divided to small and big firms using NYSE breakpoint for market capitalization. Investment level increases from top of the table to bottom, from low investing firms on the first quantile to the high investing firms in the last quantile. The operating profitability level increases from left to right. The left-hand-side variable in the regression is the excess return from each of the portfolios (Ri – Rf) and right-hand-side variables are the Fama-French five factors. RHS factor coefficients, interpreted as factor loadings are reported in the table above (a) = regression intercept, (b) = market excess return (market factor), (s) = small-minus-big (size factor), (h) = high-minus-low (value factor), (r) = robust-minus-weak (profitability factor), (c) = conservative-minus-aggressive (investment factor). For a more detailed description on LHS portfolios and factors check chapter 5.1.2 Variable construction. Regression t-values are reported on the right side of the table for each of the variables. Higher or (lower) value than 1.96 (-1.96) standing for statistical significance in a 95 % confidence interval based on simple t-test. Higher or (lower) value than 2.576 (-2.576) standing for statistical significance in a 99 % confidence interval based on t-test.

In joint results of small firms, SMB coefficients are high with an average value of (0.884) around periods. SMB increases once again coming from the second period (0.848) to third period (0.915) similar to trend what was seen on 5x5 sorts. On big firms' category, SMB is mostly insignificant variable resulting only small and mostly insignificant coefficients, as average coefficient thought periods is (-0.089) turning closer to zero from the second period (-0.099) to the third period (-0.070). On small firms' category, average absolute RMW coefficient has been increasing from the first period (0.310) with ten out of sixteen significant coefficients, to the second period (0.366) with 14 significant coefficients, and finally to (0.406) with 12 significant coefficients on the last period. These results are similar to what has been seen on sorts of size and operating profitability. Rise between periods is high and significant. Although it needs to be remembered, as average absolute values of all coefficients are used in this evaluation, and not all values were statistically significant, thus these results are only giving the direction of the trend, not the absolute magnitude of change. Same results comparing RMW coefficient on big firms differentiate a bit as average absolute RMW coefficient has varied from control period (0.329) with nine out of sixteen significant coefficients to second period (0.236) with 10 significant coefficients and to last period (0.283) with 9 significant coefficients. Although, increase at period three is visible.

Because of a low number of significant coefficients on the whole RMW table on big firms, the lowest and highest operating profitability columns are also evaluated. There are 21 out of 24 significant RMW coefficients on extreme columns of operating profitability on big firms on all tables, and a similar number for small firms is 23 out of 24 significant coefficients on operating profitability extremes. On big firms' category lowest operating profitability column shows average coefficients in the first period of (-0.597) to second period (-0.342) and to (-0.501) in the third period. On small firms', same average coefficients are (-0.647), (-0.605), (-0.803). Highest operating profitability category shows average coefficients in the first period (0.317) to second (0.314) to last (0.370). On small firms' same average coefficients (0.277), (0.456), (0.451). Based on these results on coefficients, RMW seems to be slightly more important in explaining the returns of small firms than large firms on average. RMW has much more explanatory power in the third period compared to the second period on operating profitability extremes. This is similar to findings on size and operating profitability sorts suggesting increased importance of RMW risk-factor in explaining returns.

CMA provides a bit higher absolute slopes on the third period of (0.433) with 13 significant coefficients compared to the second period (0.372) with the same number of significant coefficients on big firms. On the first period at big firms' category, the CMA coefficients were mostly insignificant. On small firm's CMA seems not to play a big part at explaining returns on average. However, extreme quantiles from each characteristic of OP and INV seem to have a couple of extreme CMA coefficients in small firms' category. As in (low OP, low INV) coefficients are (0.581) on first, (0.404) on second, and (0.404) on last. And (high OP, high INV) same coefficients (-0.384), (-0.312), (-0.396). Most extreme value can be found from the period three (table 22) (low INV, 3 OP) as coefficient is high as (0.922), but this can be seen as a bit of an outlier comparing to other coefficients. On small firm's CMA seems to variate much providing high significant coefficients or insignificant low coefficients. In addition to these findings, there are not much to add on single coefficient comparison as CMA and RMW coefficients seem to variate between the firm categories.

5.5.4 Highlights on size, operating profitability and investment tests

These return patterns in (table 18) give more evidence about the existence of operating profitability patterns in the returns showing the simple fact that more profitable firms have higher average returns. The lost size effect is found in the last period when using a broader approach to divide firms only in two size categories showing support to small firms having higher returns than big firms. Performance evaluation reveals the fact that FF5 is not as steady explaining returns in low-frequently data at shorter periods based on a test on size, operating profitability and investment sorts. Biggest problems in explaining returns are faced in different sorts of large-sized firms. This is opposite to previous studies (e.g. Fama & French, 2015) FF5 had difficulties in explaining the returns of small firms, not the big firms.

RMW coefficient loadings show more support to the higher importance of the profitability factor in explaining the returns at period three compared to the second period and the first period. High and low operating profitability columns seem to provide significant results as most of the RMW coefficients are statistically significant in both small and big size categories. Increase in absolute average coefficients seen coming to the present day as coefficients on extremes increases significantly between the second and third period. Results also reveal that RMW seems to be better explaining the returns of small firms than big firms on average. Findings are similar to the size and operating profitability 5x5 sorts suggesting increased importance of RMW risk factor in explaining average returns.

Investment average return pattern is not very much supported expect for big firms on the first two periods. CMA seems to have a high effect on explaining some returns on extremes, but on average firms, it helps little to none. Tests reveal that for small firms CMA risk factor is mainly unimportant, but for big size firms, there are much more significant coefficients despite the low performance of FF5. SMB and HML movements follow similar trends as in 5x5 sorts, and it can be clearly seen that these risk factors are much more important in explaining the returns of small firms than big firms coming to present day as coefficients of these factor decrease significantly.

6 CONCLUSIONS

The empirical part of this thesis reveals that there are significant changes in risk-factors after the financial crisis. The magnitude of changes is much higher than between the control period and period before the financial crisis. It is safe to conclude that the global financial crisis has affected the financial markets and major risk-factors significantly in the U.S. equity markets. To point out. There is a considerable decrease in the number of firms in the smallest size columns after the financial crisis at period three. On other columns the number of firms is steady. Thus, this action can be seen as a normal outcome of the crisis and not determining the results of this thesis.

The third hypothesis anticipates that visible risk factor patterns in average returns disappear after the financial crisis. This hypothesis is accepted as we see return patterns disappear on period three (after the financial crisis). Average return patterns were strongly visible on the control period and period two (before the financial crisis). Period two 120-months before the breakpoint of the end 2008 seems to be "golden" era for risk-factors as they provide significant differentiation in average return patterns similar as seen in the control period, but stronger on magnitude. Returns for risk-factors excluding the market factor were very high on the second period when comparing to the other two periods. The second period seems to be the only one where size effect on average returns is easily visible on 5x5 sorted portfolios supporting the strong presence of risk-factors on this period. Tests on 2x4x4 sorted portfolios revel side effect also in period three using broader diversification to two size groups, small and big firms.

Using financial crisis and end of 2008 as a breakpoint for data we can see that risk-factor return patterns disappear almost in all cases on 5x5 sorts at the third period of 120-months. The single expectation was a mild pattern between extremes on investment effect. Return dispersion between different categories is considerably low in the last period. This fact shows no support to the broad diversification of firms with major risk factors such as value (BE/ME), operating profitability and investments in the period after the financial crisis on 5x5 sorts. Equity markets in the U.S. seem to be overcrowded as all returns are highly positive with low dispersion between firm characteristics in the period three making differentiation firms with these risk factors not showing any previously discovered average return patterns on daily data. However, on 2x4x4 sorts, profitability effect was able to generate average return patterns between extreme categories also in period three between low and high operating profitability. Showing high profitability firms have higher returns on average in period three consistently as in earlier periods.

More significant changes are seen on the coefficients of the risk factors. First, discussing their own sorts for each of the risk factors. HML (value) factor has a negative decrease of approximately six percent of explanation power in excess returns coming to period three after the financial crisis. This change is significant, as between period one and two value effect explanatory power was slightly increasing. The financial crisis and changes shifted value to lose explanatory power. RMW (profitability) factor gains five percentage in explanation power coming to the third period nearly suggesting that value and profitability have some shifts on explanatory power. This change on RMW is low in magnitude, as between period one and two profitability factor gains much more explanatory power. However, these changes signs of the increased importance of profitability factor in last twenty years period coming to the present day. CMA (investment) is pretty steady on its own sorts, suffering no major changes, but on other sorts than its own CMA performs very weak on period three. Second, evaluating different risk factors and sorts. Other risk factors show a similar robust story in all tests. SMB (size) increases significantly coming to period three and changes on the way that SMB explains returns of small firms much better and decreases closer to zero on big firms on period three. This is one signs of increased illiquidity premium on equity markets. Market factor increases also coming to the third period after the decrease in explanation power in the second period. HML seems to lose explanation power in all sorts evaluated in this thesis suggesting the lower presence of this factor in the equity markets to the present day.

Third, evaluating 2x4x4 sorts that reveal additional information to results. On tests, RMW (profitability) coefficients show further support to the higher importance of the profitability factor in explaining the returns at period three compared to other periods. RMW has a bit higher importance on explaining the returns of small firms. Findings on the profitability factor are similar to 5x5 sorts. CMA (investment) factor seems to have a high effect on explaining some returns on extremes, but on average it helps little to none on different portfolio sorts, excluding CMA factors own sort where it performs steadily. Explaining the returns of small firm's CMA seems to be very insignificant. SMB (size) movements follow similar patterns as in 5x5 sorts revealing that this risk factor is much more important explaining the returns of small firms than big firms. Similar finding on 2x4x4 sort is made in the case of HML as it is very weak on explaining the returns of big firms.

Based on all regression tests. Importance of profitability, which is one part of quality seems to be increased from the control period and after the financial crisis. This increased importance of quality is also emphasized in other recent studies on risk factors (e.g. Novy-Marx, Asness et al.). The empirical part of this thesis shows more support to the increased importance of profitability explanatory power in average returns at present day. Literature review and regression test show support to the fourth hypothesis, there is a flight to quality after the financial crisis. This fact can be seen from increased average absolute profitability coefficients on regression tests at the same time as other major risk factors (value and investments) lose explanatory power on regression tests.

Evaluating the second hypothesis that is strongly related to the main research questions of this thesis issues the question; is the performance of the Fama-French five-factor model affected by different states on the market. This hypothesis is firmly accepted, as model performance increases significantly in period three being pretty steady between period one and two. Performance of FF5 is significantly highest in period three at all sorts and tests. Low performance of FF5 in explaining monthly returns at shorter periods on big firms was interesting as earlier studies have shown that (e.g. Fama & French, 2015) FF5 has problems in small firms, but this result can be strongly related to a low number of observations. Using daily data with a large number of observations as along with data close to the present day, FF5 works extremely well and using it in applications recommend based on these tests.

Alongside with answering the research questions, this thesis provided accurate information on what kind of returns these factors explain with the best performance and what changes different market states have had on them. Market factor and SMB seem to capture returns that other factors are not able to capture on average. This is shown from the difference between daily and monthly tests and mainly the second period (01/1999 – 12/2008) as those MKT and SMB factors are relatively low and other factors high. The second period can be seen as a period of a golden era for other factors in explaining returns as risk factors (HML, RMW, CMA) had high returns on average and explained on average returns better than in the control or the period three.

SMB (size) explains the returns of small firms with increased performance in the last period. This happens in addition to SMB losing explanatory power in big size categories as coefficients decrease closer to zero. The result shows that the average returns of small firms are more driven by the size and associated illiquidity premium on period three. Illiquidity premium is supported as regression tests reveal that the profitability of small firms decreases coming to period three. Thus, other changes in characteristics are not good in explaining similar returns of small firms compared to big firms. HML (value) explains returns of high book-to-market firms better than returns of low book-to-market firms. Performance of HML decreases in its own sort coming from second to last period. In 2x4x4 sorts, HML is lacking much of performance on explaining the returns of big firms. RMW explains returns of small and big firms on a good performance, providing slightly better performance on small firms. Increasing coefficients on its own sort supporting increasing importance of this risk factor. CMA is steady at explaining the return on both sides of extreme investing activities with similar explanatory power. However, CMA lack explaining middle categories of investment and those categories seem to have higher returns on average than extremes. High returns of middle investment categories are explained with negative RMW coefficients on extremes and positive RMW coefficients on the middle. Suggesting profitability drives more of returns than investments itself on those sorts of size and investments.

The size effect is visible on all sorts on period two and otherwise invisible, expect for 2x4x4 sorts where size effect is visible between small and big firms. Different risk factors seem to capture and explain differences in average returns between small and big firms differently. In most cases, risk factor presence increases as firm size decrease. Suggesting there is size effect, but it is not directly related to firm size, moreover to other characteristics that small firms have compared to big firms. Asness et al. (2018) find that size matters if quality or junk characteristics are controlled. Yes, but is this more of a quality factor than size factor if the effect is not visible without controlling for quality? Small firms have higher coefficients and are more explanatory in other risk factors too. Asness et al. point out that small quality firms outperform large quality firms, but they did not control for other risk factors which variate along with firms' size. Illiquidity was controlled in their tests, which revealed a much smaller magnitude size effect, and this illiquidity seems to be the driver behind size effect mostly. It is concentrated on small firms, which is seen from the SMB coefficient loadings on regression tests. This thesis finds more support to size being unimportant on other than returns of small firms. As regressions tests reveal that characteristics, risk factors variate with the firm size, moreover, supporting the fact that the size factor overlaps the other risk-factors. Asness et al. paper reveals the importance of size association with changes in other firm characteristics than characteristics directly linked to size, not supporting size as a strong risk factor in average returns.

In simple terms, results show that some risk factors such as profitability are more important in explaining returns on the present-day as some factors lose their power (value, BE/ME). The investor should focus more on these characteristics of firms on the present-day than other less important characteristics from the historical periods on equity markets. Although, it is good to remember that differences in average returns were very small in period three suggesting the task of differentiating firms with risk factors studied in this thesis is not easy, and some other factors could do a better job.

For future studies, it would be interesting to create quality factor or sorts based on quality. Quality is pointed out in many empirical studies on risk-factors, including this thesis. Including quality into asset pricing models and defining common consensus what quality means is still in progress. Future research about the different common characteristics that characterise quality firms would be demanded. Those results would allow us to differentiate firms from quality to low quality, and I strongly believe that it would allow us to see much higher dispersion in average returns than on sorts used in this thesis. Creating a common quality factor would be a good addition to asset pricing models. Also, a similar study as this thesis made to European stock market would be interesting and could provide stronger and supporting results of changes as Europe suffered more from the global financial crisis as did the U.S. economy.

APPENDIX

APPENDIX 1. AVERAGE NUMBER OF FIRMS ON SORTED PORTFOLIOS

a. (SIZE & B/M) Period one: 5135 firms on average (01/1989 – 12/1998)

	Small Size	2	3	4	Big Size
Low B/M	795	238	154	110	106
2	460	162	103	81	72
3	417	153	94	73	61
4	481	133	78	66	54
High B/M	1014	110	54	40	25

b. (SIZE & B/M) Period two: 4660 firms on average (01/1999 – 12/2008)

	Small Size	2	3	4	Big Size
Low B/M	497	180	145	132	157
2	359	143	114	94	74
3	422	143	96	69	53
4	594	136	76	52	39
High B/M	902	90	43	33	19

c. (SIZE & B/M) Period three: 3335 firms on average (01/2009 – 12/2018)

	Small Size	2	3	4	Big Size
Low B/M	266	141	99	112	113
2	203	113	93	81	76
3	244	121	76	63	51
4	338	122	73	48	42
High B/M	660	87	49	37	29

d. (SIZE & OP) Period one: 5263 firms on average (01/1989 – 12/1998)

	Small Size	2	3	4	Big Size
Low OP	1671	209	85	47	27
2	501	155	94	67	41
3	372	152	99	80	62
4	309	143	114	96	91
High OP	417	148	102	84	98

e. (SIZE & OP) Period two: 4755 firms on average (01/1999 – 12/2008)

	Small Size	2	3	4	Big Size
Low OP	1523	229	118	76	47
2	494	142	88	64	51
3	355	133	102	77	62
4	258	107	95	89	89
High OP	209	93	80	80	95

f. (Size & OP) Period three: 3389 firms on average (01/2009 – 12/2008)

	Small Size	2	3	4	Big Size
Low OP	954	174	79	51	28
2	314	135	91	66	47
3	218	118	88	67	61
4	137	85	69	75	90

High OP	122	81	69	86	86

g. (SIZE & INV) Period one: 5206 firms on average (01/1989 – 12/1998)

	Small Size	2	3	4	Big Size
Low INV	957	118	54	48	33
2	416	114	79	70	69
3	388	119	93	79	76
4	449	160	109	85	76
High INV	1008	287	157	95	66

h. (SIZE & INV) Period two: 4905 firms on average (01/1999 – 12/2008)

	Small Size	2	3	4	Big Size
Low INV	884	123	77	60	45
2	412	106	71	67	63
3	431	123	87	74	73
4	460	145	103	84	77
High INV	747	233	162	111	88

i. (Size & INV) Period three: 3550 firms on average (01/2009 – 12/2008)

	Small Size	2	3	4	Big Size
Low INV	591	107	62	49	38
2	285	97	74	62	65
3	236	100	74	72	75
4	279	123	89	84	77
High INV	459	192	109	85	66

j. (Size & OP & INV) Period one: 4057 small firms and 905 big firms on average (01/1989 – 12/1998)

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	636	119	73	106	58	46	45	41
2	276	193	160	148	53	57	52	42
3	206	213	230	204	51	57	62	55
High INV	533	264	293	402	69	53	75	88

k. (Size & OP & INV) Period two: 3739 small firms and 945 big firms on average (01/1999 – 12/2008)

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	691	114	80	96	77	46	39	46
2	274	172	153	107	56	53	50	45
3	231	219	232	168	48	59	64	53
High INV	507	220	236	240	106	65	71	65

l. (Size & OP & INV) Period three: 2529 small firms and 840 big firms on average (01/2009 – 12/2008)

	SMALL				BIG			
	Low OP	2	3	High OP	Low OP	2	3	High OP
Low INV	411	85	60	75	65	40	37	51
2	189	148	116	91	46	48	49	47
3	141	179	160	94	42	58	53	51
High INV	314	168	152	144	76	61	60	57

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