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Essays on Factor Investing

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Preface

"There is only one way to eat an elephant, one bite at a time". Desmond Tutu, a Nobel Prize for Peace laureate, used this signature phrase to describe his unbridled efforts against the apartheid. This metaphor utterly describes my view on the life of a PhD-candidate. Having the big picture in mind but focusing on the little wins every day is what makes the difference between ultimate success and abject failure. It has been four years of tremendous efforts which reshaped my life in so many positive ways. Without a doubt, I have learnt a lot from the people around me, and all of them have left a unique footprint on me and consequently on this thesis. I would like to express my deep appreciation to a few people in particular.

First and foremost, I am deeply indebted to my supervisor Joop Huij. Few people have the privilege to be supervised by their life mentor, and I consider myself lucky enough to be one of them. Joop, your genuine passion for research sparked my long-lasting interest which was the necessary fuel in completing this thesis. Your persistent focus on the big ideas, mixed with detailed technical knowledge, is a hard-to-find combination. During the course of the last four years, we spent numerous evenings next to a steaming barbeque, optimizing the perfect temperature for a tenderloin, and occasionally appreciating a good cigar. However, next to the heated coal we also engaged in heated discussions about reshaping the financial industry. It is this level of ambition which kept me going the extra mile and resulted in significant improvements in all chapters in this thesis. Thank you for making me a better researcher!

I would like to extend my gratitude to my promoter Marno Verbeek who made all this possible. He provided the right platform for successfully completing this thesis. Marno, you always ensured that I am going in the right direction but at the same time gave me the necessary freedom to show creativity. You helped me successfully combine a full-time PhD position with my job in the financial industry which is greatly appreciated! Special thanks goes to the members of my reading committee Stephen Schaefer, Tom Steenkamp, and

Mathijs van Dijk. Your invaluable comments on my work have certainly added the extra spice in this thesis and significantly improved its academic impact.

Next, I would like to thank my colleagues at Robeco and Rotterdam School of Management. I am extremely grateful to Simon Lansdorp who first opened the door to the investment industry for me. Simon, thank you for being instrumental in my development as a researcher. We have come a long way since the beginning but we are still working together just as passionately. It is true pleasure! Viorel Roscovan, thank you for helping me develop the invaluable writing skills every PhD candidate needs. Milan Vidojevic, we started our PhD trajectories together and have been like blood brothers ever since. Amr Albialy, I am honoured by the opportunity to learn from your interpersonal and commercial skills. Their influence is felt on all aspect of my life. Jeroen van Zundert, no one could master my programming skills better than you. Jose Albuquerque de Souse, thank you for sharing with me countless hours around the coffee machines at RSM. Marta Szymanowska, teaching a course with you was an invaluable experience. Daniel Haesen, Jean-Paul van Brakel, Patrick Houweling, Martin Martens, David Blitz, Pim van Vliet, and everyone else who has been working closely with me during the past four years, thank you for your practical advices, constructive criticism, and insightful suggestions.

The completion of this thesis would not have been possible without the silent support and unconditional love of my family - my mother Nadezhda, father Stefan, and brother Nikolay. Mother, you thought me to make my own decisions and bear the consequences from an early age and this decisiveness has turned into the driving force of my character. Father, thank you for being my most supportive ally and most fearsome sports rival! Our sport games have shaped my competitive spirit which eventually led me to pursuing a PhD degree. Brother, thank you for being my closest friend and supporting me at every step.

I cannot begin to express my appreciation to Svetoslava who is always by my side during the difficult moments. Thank you for being my biggest source of motivation and for filling my life with true meaning! Finally, I would like to thank our unborn son for giving me the extra push in finalizing this thesis!

Georgi Kyosev
Rotterdam, March 2019

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Chapter 1

Introduction

Beating the market is easy! Seemingly simple long-only equity strategies defined by using widely available public information outperform the S&P 500 index by a margin of more than 3% per annum[1]. Why do then professional investors fail to do so, as suggested by Carhart (1997)? The answer to this question requires a deep dive in the origin, development, and rise of factor investing.

Factor Investing[2] is a recent terminology used to describe the process of transforming academic knowledge into real investing strategies. As such, it has a relatively short history and to a great extent is triggered by the recent turmoil during the 2007-2009 financial crisis and the subsequent study of Ang, Goetzmann, and Schaefer (2009) who show that 70% of the Norwegian Government Pension Fund's return can be attributed to systematic exposure to academically documented factor premiums. To fully understand how factors changed the global investment landscape we need to go back to the origin of asset pricing. The rest of the chapter provides a brief description of the primary theoretical and empirical studies as well as market events that influenced the recent state of factor investing, in a chronological way.

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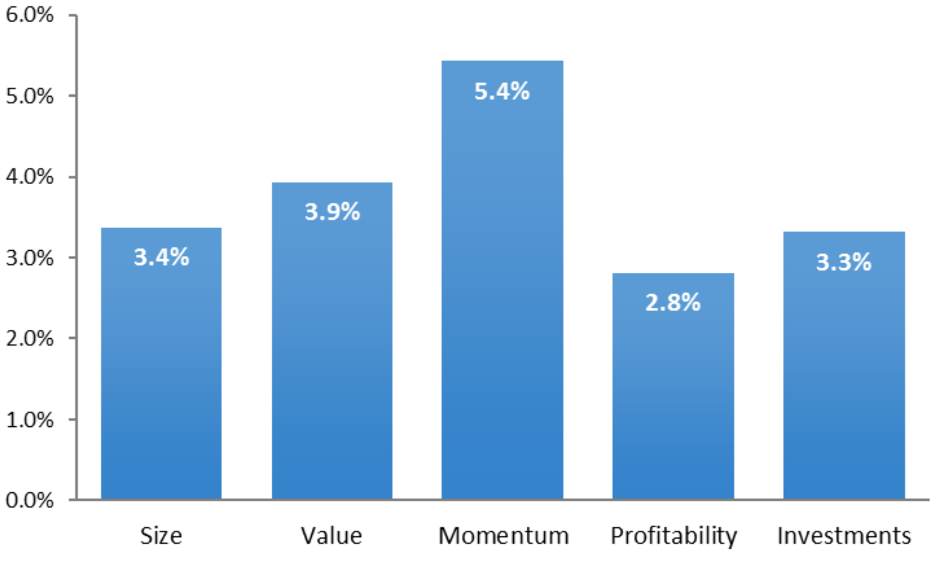
[1] Benchmark adjusted returns per factor are shown in Figure 1.1

[2] In this thesis the use of factor investing is limited to the equity space. We discuss factors which are popular both in academia and the industry. Based on our classifications these are the market, low beta, size, value, momentum, and accounting-based factors such as profitability and investments. The term 'quality' is used as wrapper for accounting-based factors. Chapter 3 is fully dedicated to the precise definition of this factor.

Figure 1.1 Returns of long-only factor portfolios in excess of the market return

The figure shows long-only returns of U.S. equity portfolios, as downloaded from the Kenneth French Data library. Returns are calculated in excess of the market returns, annualized, and measured in U.S. Dollars. The sample period is Jul-1963 – Aug-2018. Value, Momentum, Profitability, and Investments are based on six value-weighted portfolios sorts as the average of small attractive and big attractive portfolio. For example, Value is the average of 'small - high book-to-price' and 'big - high book-to-price' portfolios. Size is the average of the small value, small growth, and small middle portfolio based on 6 'size – book-to-price' sorted portfolios.



In their thorough overview, Dimson and Mussavian (1999) provide a detailed description of asset pricing studies dating back to the work of Daniel Bernoulli (1738). The aim of this chapter is not to provide a similarly detailed overview of asset pricing studies but to identify the key events and academic publications which lead to the rise of factor investing in the recent past.

A brief timeline of studies which affected the rise of factor investing:

1930s – 1960s: Market efficiency

- Return predictability, Cowles (1933)
- Efficient Markets Hypothesis, Fama (1965)

1950s – 1970s: First theoretical asset pricing models

- Mean-variance portfolio optimization, Markowitz (1952)
- Capital Asset Pricing Model (CAPM), Sharpe (1964), Lintner (1965)
- Arbitrage Pricing Theory, Ross (1976)
- Intertemporal CAPM and Consumption-based CAPM

1970s – 1990s: First empirical tests

- Low-beta effect, Black, Jensen, and Scholes (1972)
- Value effect, Basu (1977) and Stattman (1980)
- Size effect, Banz (1981)
- Fama and French three-factor model, Fama and French (1993)
- Momentum effect, Jegadeesh and Titmann (1993)
- Accruals effect, Sloan (1996)

1990s – 2009: Source of factor premiums and mutual fund returns

- Institutional investors and asset prices, Lakonishok, Shleifer, and Vishny (1992)
- Betas versus characteristics, Daniel and Titman (1997)
- Performance persistence in mutual funds, Carhart (1997)

2009 - present: The rise of factor investing

- Norwegian reserve fund – Ang, Goetzmann, Schaefer (2009)
- Growth in assets of mutual funds managing factor-based strategies

1.1. Overview of asset pricing literature

Market efficiency

Analyses involving testing the historical profitability of hypothetical investment strategies are only the tip of the iceberg. Understanding why they perform in certain ways boils down to understanding how are the underlying securities priced. Or put in other words, are there certain mispricings that can be exploited by informed investors. The body of literature which deals with the degree to which information is incorporated in market prices is typically referred to as market efficiency literature. While the debate on the exact level of market efficiency is still progressing, the consensus is that even professional investors have difficulties generating positive risk-adjusted returns.

Market efficiency is the backbone of asset pricing and is thought at every university around the world. Malkiel and Fama (1970), Dimson and Mussavian (1998) and Ang, Goetzmann, and Schaefer (2011), amongst others, provide a detailed overview of most influential studies through time. We only focus on the ones that in our view had the most pronounced impact on the rise of factor investing. The foundations are set by Cowles (1933) and Cowles and Jones (1937) who show that beating the market by stock picking is a daunting task as even professional forecasters fail to outperform strategies based on random stock picks. This observation is formalized in the theory of random walk in stock prices. In his 1965 and 1970 studies, Eugene Fama formalizes the efficient market hypothesis and extends it by introducing multiple levels of market efficiency depending on the type of information which is incorporated in stock prices. Weak form efficiency entails that prices incorporate all past price information. Semi-strong form efficiency entails that all public information is incorporated in prices. Strong form efficiency entails that all information, public and private, is incorporated in prices. Even though the strong form market efficiency hypothesis is taking it to the extreme, the evidence presented in Fama (1970) builds a strong case for weak- and strong-form market efficiency.

The concept of market efficiency is crucial for the origin of factor investing as most of the factors that investors recognize today have been discovered during tests on the efficiency of the market. Even more, all asset pricing models based on which factors are classified as "anomalies" have been developed in the context of market efficiency. As such, profits due to mispricing are largely discarded in academic studies, and higher risk is deemed as the only feasible source of higher return. Due to the paramount importance of market efficiency on all aspects of asset pricing, Chapter 2 of this dissertation provides a novel test on the slope of demand curves for stocks which can be used as direct evidence in relation to the efficiency of financial markets.

First theoretical asset pricing models

Market efficiency stipulates that all available information is incorporated in prices. This does not necessarily imply that all stocks have the same expected return. But if all stocks are fairly priced and at the same time have differing rates of returns there might be a common factor which affects these rates of return. Even though theoretical researchers largely agree that the common factor driving asset prices is risk, the notion of risk has evolved significantly through time. In his seminal paper, Harry Markowitz (1952) sets the foundations of modern portfolio theory. He shows that under the assumption, amongst others, that all investors are mean-variance optimizers they should all hold the optimal risky portfolio, or put in other words. The only aspect which differs among investors is the amount of wealth held in the optimal risky portfolio. The remaining is invested in the risk-free asset. The exact allocation between the risky and the risk-free assets are determined by the risk tolerance of investors. As such, the only way to command a higher expected return is to bear higher levels of risk.

Sharpe (1964) and Lintner (1965) build on the portfolio theory of Markowitz and prove that, under their assumptions, in equilibrium, the optimal risky portfolio is the market portfolio. In the Capital Asset Pricing Model (CAPM) the expected returns of assets are a linear function of their systematic risk measured by their market beta, where beta captures the contribution of an asset to the market risk as a fraction of the total market risk. Under CAPM only systematic risk is rewarded with a return premium and expected return is a linear function of market beta.

Even though CAPM has a tremendous impact on how investors analyze stock prices today it is burdened by its strong assumptions and does not allow for an additional source of systematic risk next to the market risk. This critique has been addressed by Ross (1976) and his Arbitrage Pricing Theory (APT). It relaxes most of the assumptions of CAPM and is based on the no-arbitrage condition. In case of mispricing, the activity of arbitrageurs is sufficient to drive stock prices back to their fundamental values at which expected return is only determined by the underlying risk. The notion of underlying risk is also improved as APT allows for multiple sources of systematic risk. However, it does not specify what precisely these factors are, which limits its practical applicability. Another major critique of APT is that arbitrage can be difficult in practice due to, for example, short sale or borrowing constraints. Shleifer and Vishny (1997) propose a framework which allows for limits to arbitrage and show that prices can deviate from their fundamental values for long periods of time. The ICAPM of Merton (1973) is another attempt to extend the CAPM with more realistic assumptions about market dynamics. It extends the model to a multi-period horizon and infers that apart from end-period total wealth, investors care about the shocks in future consumption, trying to smooth the overall lifetime consumption.

First empirical tests

The enormous success of the Capital Asset Pricing Model triggered a wave of empirical studies attempting to falsify it. Perhaps the most common methodology for testing whether market beta is the only return predictor is to sort stocks into portfolios based on a particular characteristic and show if the historically realized return of each portfolio deviates from the one predicted by the portfolio's beta. Some of the first empirical tests on CAPM have been performed by Black, Jensen, and Scholes (1972) who show that the relationship between market beta and return is positive but flatter than implied by CAPM. Their finding suggests that lower beta stocks appear to be underpriced and thus have positive alpha relative to the market model. Stock characteristics which can be used to generate positive alpha are referred to as 'anomalies' indicating deviation from the risk-return relationship and potential evidence against the efficiency of financial markets. One of the first documented anomalies is the size effect of Banz (1981) who show that firms with small market capitalization generate abnormally high returns given their betas and the opposite holds for firms with high market capitalization. Other early anomalies are the earnings to price effect of Basu (1977) and the book to price effect of Stattman (1980). Subsequently, anomalies which compare a fundamental value such as earnings or book values of companies to their market values are commonly known as the value effect. The size and value effects proved so robust that in their seminal paper Fama and French (1993) proposed an alternative factor model which augments the market model with proxies for the size and book to market factors. They justify the addition of the two new factors to the asset pricing model by claiming that they capture non-diversifiable risks in the economy which are rationally compensated with a return premium. The so-called Fama and French three-factor model successfully explains the majority of documented CAPM anomalies and is widely used even today as a reference benchmark in mutual fund performance evaluation. One anomaly which remained unexplained by the three-factor model is the momentum effect of Jegadeesh and Titman (1993) who show that stocks with high past returns generate abnormally high future returns. In a later study, Carhart (1997) augments the Fama and French three-factor model with a momentum factor and successfully explains a big portion of the persistence in mutual fund returns. Size, value, and momentum factors have been dominating the empirical asset pricing literature over the past few decades. However, recently two additional factors, namely high profitability (Novy-Marx, 2013) and low investments (Cooper, Gulen, and Schill, 2008), are considered of similar importance. To account for them, Fama and French (2015) made their first enhancement of the previous three-factor model by also including proxies for the investments and profitability factors. However, this model still fails to explain the accruals effect documented by Sloan (1996) which leaves a gap in the current state of the literature related to the abnormal performance of accounting based firm characteristics. Chapter 3 of this dissertation provides a thorough overview of accounting based factors and aims to shed more light on the common driver of their returns.

Source of factor premiums and mutual fund returns

The mounting empirical evidence that specific strategies can generate returns above and beyond the ones expected under CAPM triggered a new wave of research. The so-called anomalies can have a significant impact on financial theory if their source is well understood. On the one hand, if the source of 'anomalous' returns relative to CAPM is driven by exposure to systematic risks, uncaptured the by market beta then the efficient markets hypothesis is intact. On the other hand, if the source of abnormal returns is mispricing, there would be further implications for the EMH. Most of the early empirical studies on factor premiums advocate for the risk-based explanation. Berk (1995) links size-related anomalies to an unobservable systematic risk factor. This notion is also shared by Fama and French (1992) who state that the value effect, measured by book-to-price, is a proxy for distress risk in the economy. They manage to explain international value returns by augmenting the single factor market model with a proxy for distress risk.

Daniel and Titman (1997) first propose a systematic approach that formally tests whether market anomalies are indeed driven by exposure to non-diversifiable factors. They conduct a 'horse race' between factor loadings and characteristics and show that it is characteristics that drive abnormal returns and not factor loadings. Their findings sparked a new idea that factor premiums can be captured without bearing additional systematic risk. These results are reinforced by the recent work of de Groot and Huij (2018) who show that value portfolios with lower levels of distress risk outperform those with higher levels of distress risk, casting more doubt on the risk-based explanation of market anomalies. Perhaps the most convincing evidence of the distress risk hypothesis is the existence of the momentum factor itself due to its negative correlation to value. Similar conclusions can be drawn from profitability and investments factors which also correlate negatively with the proposed distress factor. As a result, Novy-Marx (2013) and Fama and French (2015) propose a novel way of explaining why value, profitability, and investments effects exist by using the dividend discount model as a theoretical base. One limitation of their approach is that the dividend discount model assumes that future profits are taken into account while most of the profitability measures are based on proxies for past profitability.

The above evidence leaves a gap in the current state of the literature in relation to the reasons why firm quality-related characteristics are associated with abnormal returns. In Chapter 2 we provide a comprehensive overview of the commonly used quality definitions and test their predictive power for stock returns. We show that quality measures predict stock returns if and only if they forecast earnings growth, and that this information is not contained in other characteristics that have been shown to drive expected returns of stocks.

Barber, Huang, and Odean (2016) use flows to mutual funds to analyze whether investors perceive factor returns as risk driven or as alpha. They document that investors see market risk as the main systematic risk and consider factor returns as abnormal, subsequently rewarding funds which generate them with positive flows. Lakonishok, Shleifer, and Vishny (1992) raise a different explanation of asset pricing. They document that institutional investors trading behavior has an impact on the way prices are determined. Later in Lakonishok, Shleifer, and Vishny (1994), they propose an alternative explanation of the long-standing existence of value effect. The authors claim that institutional investors are fully aware of the existence of premiums in certain market segments, specifically focusing on value. However, being on the other side of the trade is more rational for them given their specific environment. Growth stocks tend to be more familiar to their clients; consequently, trades in the growth segments are easier to justify. This evidence is another alternative explanation of factor premiums which does not fall into the risk-based explanation, triggering even more questions on what is actually driving factor premiums.

Robustness of factor premiums

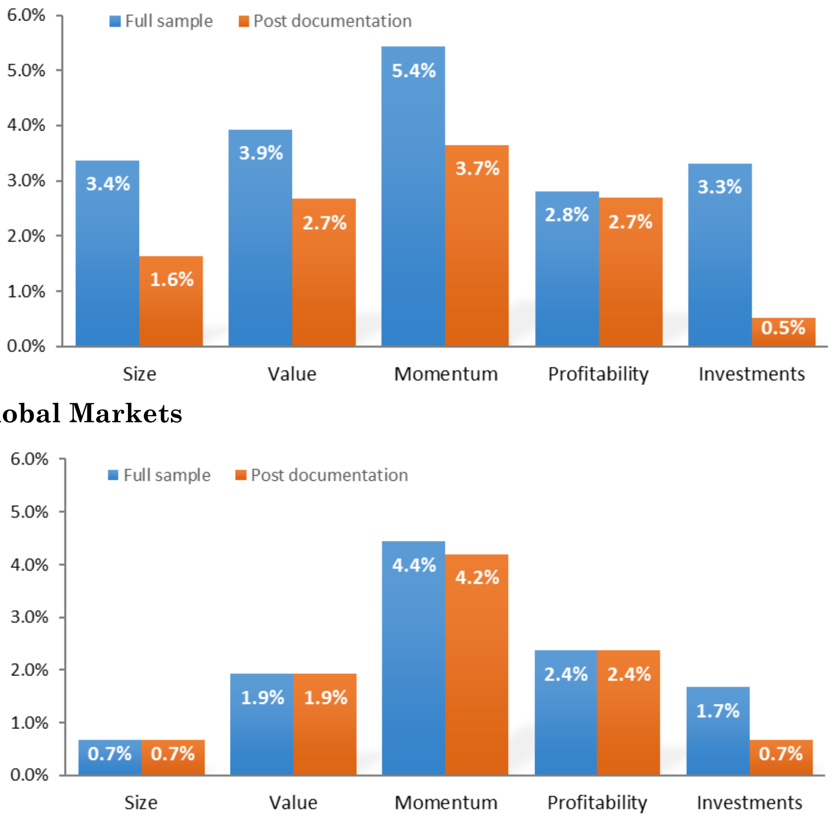
After we summarized the academic literature describing factor premiums and their underlying drivers, we show the performance of the most prominent factors as described in Carhart (1994) and Fama and French (2015). For robustness, we show long-only returns in both U.S. and Global Markets. Furthermore, we show the post documentation returns. These are the returns from the date the anomaly was first published in an academic journal till present days. Figure 1.2 illustrates the results. It highlights the robustness of factor premiums. Both, over the full sample and post documentation, in the U.S. and Global markets, premiums are positive and economically significant. The positive 'post documentation' premiums indicate that simple mispricing is unlikely to be the source of premiums. Otherwise, they would quickly be arbitraged away after the effects are published and publicly available. As such, the more likely mispricing explanation is the one put forward by Lakonishok,

Figure 1.2. Factor premiums before and after their first publication dates

The figure shows long-only returns of U.S. and Global equity portfolios, as downloaded from the Kenneth French data library. Returns are calculated in excess of the respective market returns, annualized, and measured in U.S. Dollars. Value, Momentum, Profitability, and Investments are based on 6 value-weighted portfolios sorts as the average of small attractive and big attractive portfolio. For example, Value is the average of 'small - high book-to-price' and 'big - high book-to-price' portfolios. Size is the average of the small value, small growth, and small middle portfolio based on 6 'size – book-to-price' sorted portfolios. The full sample period is Jul-1963–Aug-2018 for U.S. and Nov-1990–Aug-2018 for Global markets. Post documentation period is starts in Jan-1982 for Size (Basu, 1981), Jan-1978 for Value (Basu, 1977), Jan-1994 for Momentum (Jegadeesh and Titman, 1993), Jan-1995 for Profitability (Lakonishok, Shleifer, and Vishny, 1994), and Jan-2005 for Investments (Titman, Wei, Xie, 2004). If full sample starts after documentation date, then full sample and post documentation returns are the same.

A: United States

B: Global Markets



Shleifer, and Vishny (1994) where investment decisions are taken from a delegated portfolio management point of view. While this behavior is fully rational, it looks irrational from a mean-variance point of view and creates 'anomalies' relative to prominent asset pricing models. Chapter 3 of this thesis fully focuses on explaining the underlying driver of the quality premium and Chapter 4 provides detailed analysis on the practical applicability of factor investing strategies by looking at mutual fund performance and investor returns.

1.2. The rise of factor investing

Factor investing is a logical continuation of an evolving interrelationship between asset pricing research and the investment industry. Naturally, finance theory directly influences the way performance is evaluated, resulting in a constant evolution of the perception for an optimal investment strategy.

Passive Investing

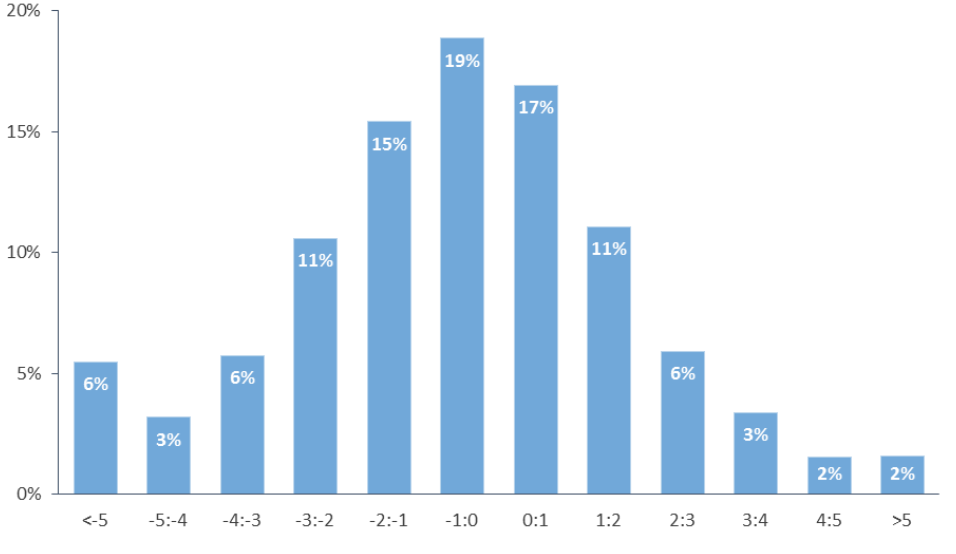
At the time of Markowitz (1952), the primary objective of fund managers has been to provide a well-diversified portfolio. Their performance has been evaluated based on total risk and return. The industry completely reshaped after Sharpe (1964) and Lintner (1965) introduced the concept of market beta. The fact that a significant exposure of fund return can be attributed to broad market movements implies that the return driven by the market cannot be attributed to manager's skill. As such, managers are evaluated based on their outperformance. To measure outperformance, investors accommodated the use of benchmarks, as proxies for market return, and investment performance started to be evaluated based on the excess return over a specific benchmark. This gave rise to a wave of academic studies analyzing the ability of managers to outperform their benchmarks. First, Treynor (1965), Sharpe (1966), and Jensen (1968) present evidence that active managers fail to outperform their benchmarks. This fact gave birth to a new way of investing called passive investing. Passive strategies are meant to replicate the performance of market capitalization weighted indices in a transparent, low-cost manner. In this way, investors are able to harvest the equity premium without the need to select an active manager and pay the higher fees associated with it. The idea materialized when in 1971 Wells Fargo Bank launched the first index fund. Passive investing continued to shape up when Vanguard was found in 1975 with the sole purpose of offering index strategies. Their first index fund was launched in 1976. Passive investing existed ever since but remained a niche product for the next twenty years. The seminal paper of Sharpe (1991) who formally shows that active management is a negative sum game after fees gave the necessary push for passive management. The Vanguard index fund reached one billion shortly afterwards in 1998. Since then passive management continued to grow, reaching 37% of all assets by the end of 2017, according to Anadu et al. (2018).

Factor Investing

Despite the rapid growth of passive investing 63% of the equity market is still invested in active mutual funds. This essentially shows that asset owners actively decide to invest against the odds, given the academic evidence that active managers underperform their benchmarks after fees. Figure 1.3 shows the distribution of U.S. mutual funds' CAPM alphas. In line with previous

Figure 1.3: Distribution of mutual fund alphas

The figure shows distributions of annualized fund alphas across all U.S. funds in the CRSP Mutual Fund Database with total assets above USD 5 mln. Alphas are calculated per fund as the intercept from CAPM regressions over all available observations during the sample period Jan. 1990 – Dec. 2015. Full sample details are described in chapter 4. '<-5' shows the percentage of funds with annualized alphas less than -5%, '-5:-4' shows the percentage of funds with annualized alphas between -4% and -5%.

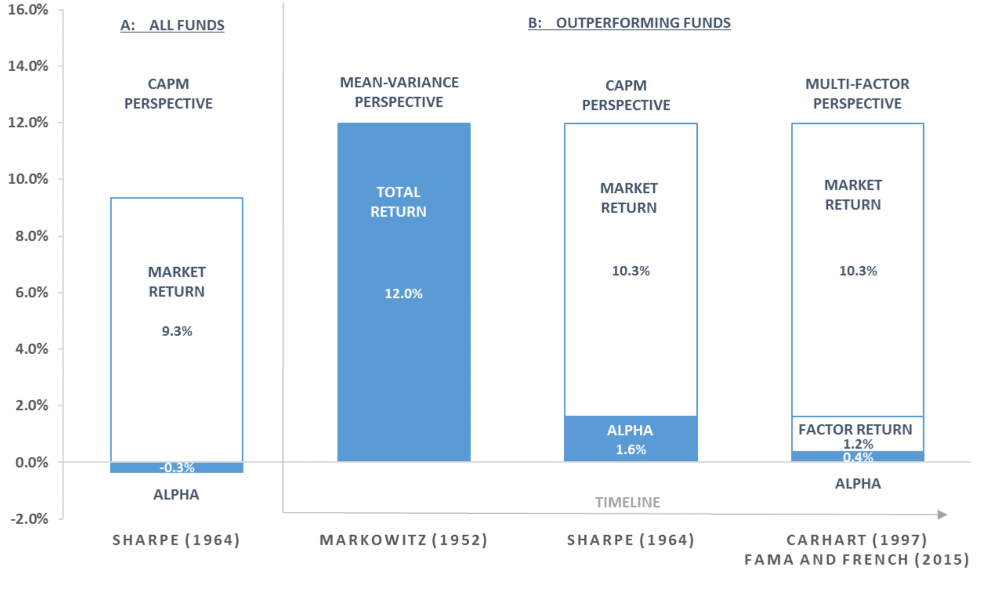


results, 59% of U.S. mutual funds underperform the market portfolio on a beta-adjusted basis. On the other hand, 41% outperform their benchmarks, and 2% of managers outperform with more than 5% per annum. Therefore, even after the rapid growth of passive investing, active management continued to be of vital importance.

Figure 1.4A shows the performance of the asset-weighted portfolio of all U.S. domestic long-only mutual funds during the period 1990-2015. Consistent with Figure 1.3 and previous studies it provides a negative alpha of -0.3%. Figure 1.4B focuses on an asset-weighted portfolio, based only on outperforming

Figure 1.4: Active return relative to prominent asset pricing models

The figure shows the annualized active return, as defined by alternative asset pricing models, all U.S. domestic, long-only equity funds in the CRSP Mutual Fund Database with total assets above USD 5 mln. Alphas are calculated per fund as the intercept from regressions over all available observations during the sample period Jan. 1990 – Dec. 2015. Full sample details are described in chapter 4. In CAPM perspective alpha (active return) is calculated relative to the market portfolio, using the following regression $R_{i,t} = \alpha_i + \beta_i \cdot (R_{M,t} - R_{f,t}) + \varepsilon_{i,t}$. In multi-factor perspective alpha is calculated using the Fama and French (2015) 5-factor model augmented with Momentum as follows: $R_{i,t} = \alpha_i + \beta_i \cdot (R_{M,t} - R_{f,t}) + s_i \cdot SMB_t + h_i \cdot HML_t + w_i \cdot WML_t + r_i \cdot RMW_t + c_i \cdot CMA_t + \varepsilon_{i,t}$. Factor return is calculated as the sum all the product of factor loadings and annualized factor returns. Outperforming funds are funds with higher returns over their respective benchmarks during the same period they existed.



funds, and decomposes its performance into underlying components. The three bars follow the historical evolution of performance evaluation as seen from multiple perspectives – (i) Markowitz (1952) total return perspective, (ii) Sharpe (1964) CAPM perspective, and (iii) Carhart (1997) / Fama and French (2015) multi-factor perspective.

First, in the Markowitz (1952) mean-variance world the return of 12.0% is the critical evaluation criterium, together with the volatility of returns. Second, under CAPM the added value of the same group of managers amounts to only 1.6% per annum. The remaining 10.3% is driven by broad market movements and can be obtained by a low cost passively managed portfolio. Finally, in a multi-factor setting 1.2% out of the 1.6% is attributed to exposure to systematic factors - market beta, size, value, momentum, profitability, and investments. The remaining active return attributable to manager skill is only 0.4%. This decomposition shows that selecting a manager who possesses true skill has become increasingly difficult with time. Even if investors are able to identify which manager is going to outperform, the potential added value attributable to true skill is only 0.4% while return due to easily measurable fund attributes, such as factor exposures, is three times higher (1.2%). In chapter 4 we show that the probability of outperforming its benchmark for a fund with no positive factor exposures is only 17% while it is 88% for a fund with exposure to four or more factors.

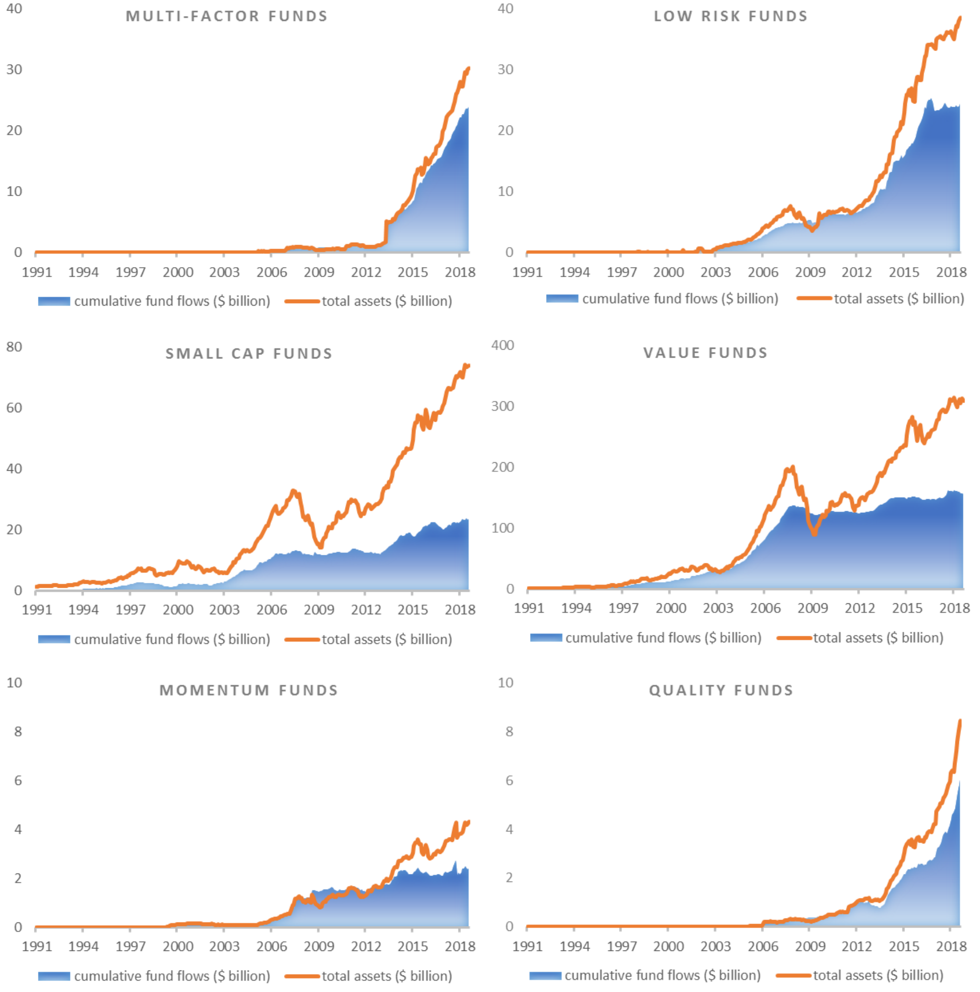
Similar to passive investing, factor investing did not grab investors' attention immediately. Even though early adopters such as Dimensional Fund Advisors provide direct access to the small cap and value premiums since the 1980s, it was only after the global financial crisis of 2007-2009 and the subsequent report of Ang, Goetzmann, and Schaefer (2009) that factor investing began to gain broader popularity. Norwegian Government Pension Fund – Global is managed by active manager selection. Despite that, Ang, Goetzmann, and Schaefer show that 70% of its active return can be attributed to systematic factors. Numbers, very similar to the ones shown in Figure 1.3, where 1.2% out of 1.6% alpha is attributed to systematic factor exposures which amounts to 75%. This made investors realize that it is more efficient to strategically allocate to factors rather than ending up with similar factor exposures based on bottom-up manager selection. As such, factor investing became increasingly popular and funds that target specific exposures to those factors started to exist.

Figure 1.5 provides a detailed description of the growth in factor investing. It looks at the asset growth in both Global and U.S. equity funds through time. Figure 1.4A focuses on global long-only equity mutual funds and exchange-traded funds, and Figure 1.4B – on U.S. long-only domestic equity mutual funds and exchange-traded funds. Conclusions in both markets are remarkably consistent. Funds with multiple factor exposures started to exist in the late 1990s but did not grow in assets until 2012. Their growth rate increased right after that, reaching assets under management of around 30 billion U.S Dollars in Global markets and 40 billion in the U.S. six years later. Low-risk funds exhibited a similarly pronounced growth rate. Their total asset base grew from sub 10 billion (20 billion) in Global markets (U.S.) in 2012 to more than 40 billion (70 billion) by August 2018. The fact that companies such as Dimensional Fund Advisors started to offer explicit small-cap and value strategies in the 1980s influenced the popularity of these factors in the investment industry. More funds, including fundamentally managed funds, started to offer similar strategies and by 2018 these two groups of funds are the biggest ones among factor-based strategies. Value funds have a combined asset pool of more than 1.5 trillion in both U.S. and Global markets. However, since 2007 growth in value strategies has been mainly driven by market returns as new fund flows have been virtually zero. The most recently documented factors - momentum and quality - also started to be adopted after the financial crisis but their asset base is still relatively small.

Figure 1.5: The rise of factor funds through time

The figure shows total assets under management and cumulative fund flows in billion U.S. Dollars of all U.S. domestic, long-only equity funds and ETFs and Global long-only equity funds and ETFs during the sample period Jan.1991– Aug.2018 in the Morningstar Mutual Fund Database. Factor funds are classified as 'strategic beta' ETFs or mutual funds containing low risk, small cap, value, momentum, quality, or multi-factor in their name. For example, if a fund contains the word 'momentum' in its name it is classified as a momentum fund.

A: Total assets and cumulative fund flows in billion U.S. Dollars – Global funds



B: Total assets and cumulative fund flows in billion U.S. Dollars – U.S. funds

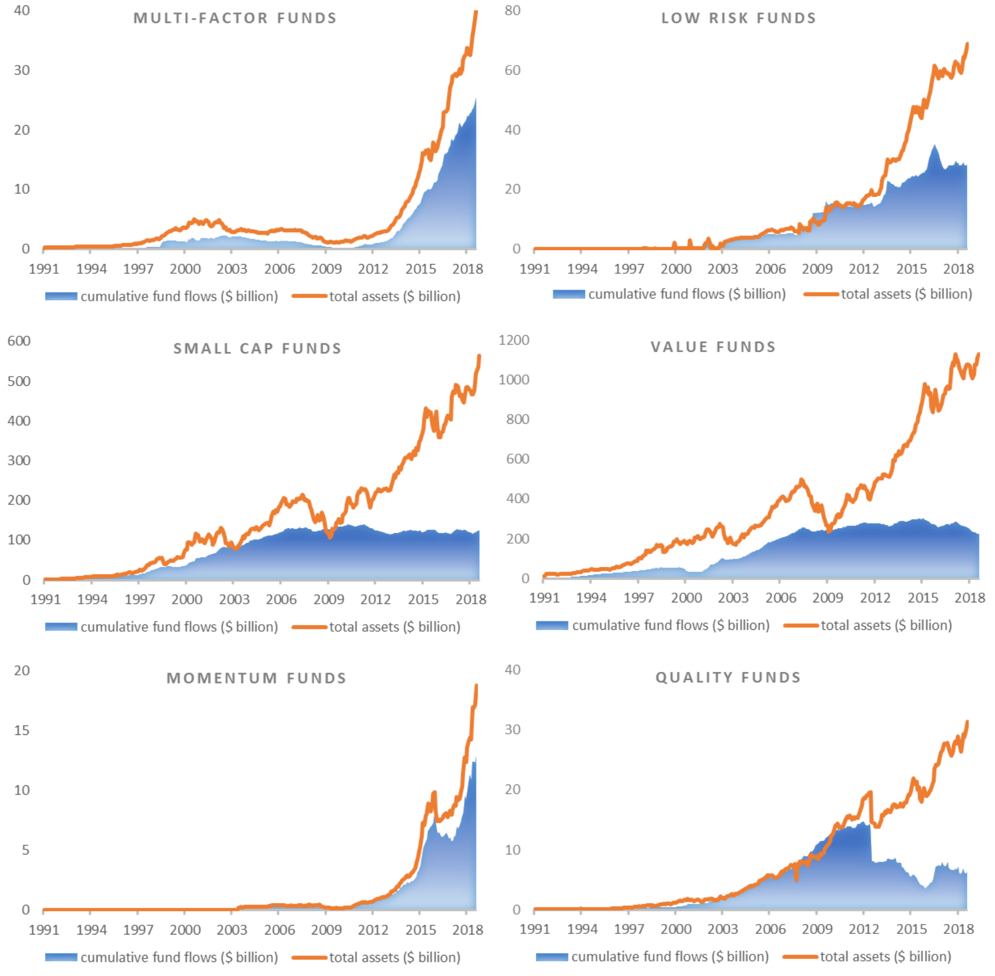


Figure 1.6 presents another way to visually illustrate the growing interest in factor investing. It measures the amount of interest of individual people by measuring the google searches for terms associated with factor investing. Similar to the growth of factor funds, the alternative analysis confirms the notion that it was only in recent years when factor investing became popular for the broader audience.

Figure 1.6: Google Trends search interest for factor investing

The figure shows the search interest in Google Trends for factor investing. Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means that there was not enough data for this term. The graph is calculated as the average of search interest for 'factor investing' and 'smart beta', typically used interchangeably in the industry. Then the rolling window twelve-month average is reported on the figure.

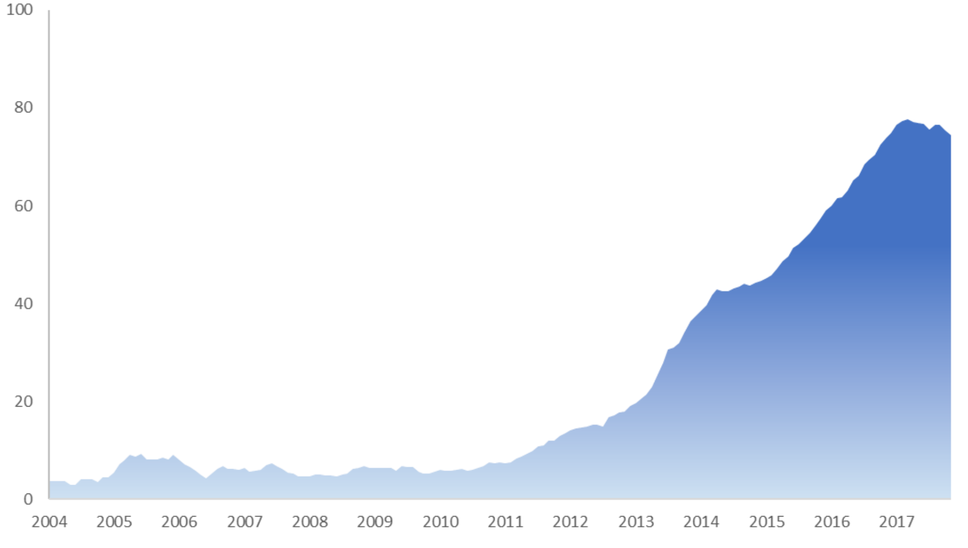
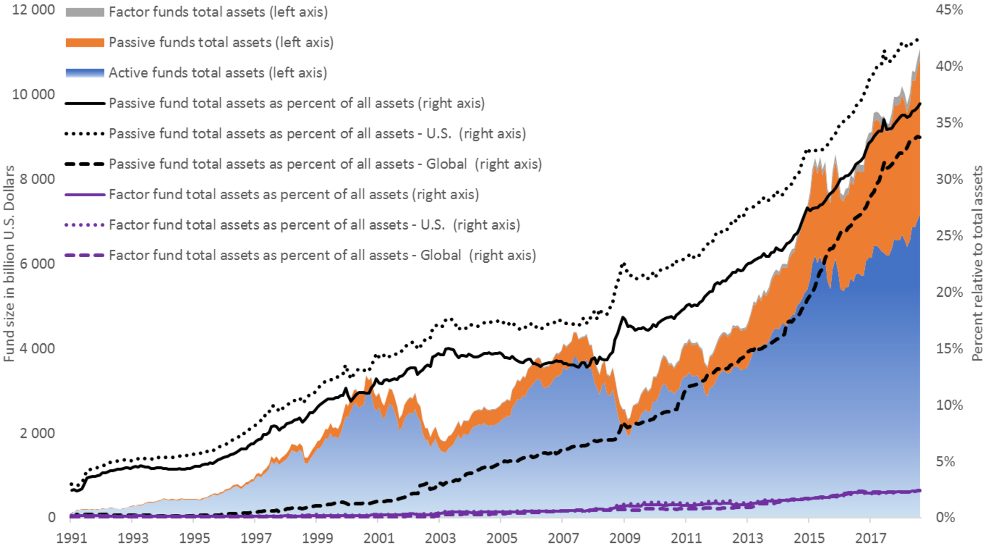


Figure 1.7 puts everything in perspective. It looks at the two broad waves in the investment industry simultaneously. Namely, it shows that growth in factor investing in the context of passive investing. The figure combines all U.S. and Global long-only mutual funds and ETFs and plots the combined total growth. By August 2018 the total assets of all funds are 11 trillion U.S. Dollars as active funds (blue area) contribute around 7 trillion, passive funds (orange area) – around 3.5 trillion, and factor funds (grey area) – 0.25 trillion. The solid black line, measured on the right axis, shows the percentage of passively managed assets versus all assets through time. Consistent with the high-level overview at the beginning of this section, it shows that passive funds started to gain popularity in the early 1990s and their exponential growth continued ever since. Passive funds composed around 5% of all assets in 1991 and 37% in 2018. The dotted and dashed black lines split this growth into the one in the United States (dotted line) and the one in Global markets (dashed line). The two show

that passive investing first picked up in the United States in the early 1990s and started to grow in Global markets around 10 years later. The early adoption of passive investing in U.S. is largely driven by the success of Vanguard Group.

Figure 1.7: Total assets under management in billion U.S. Dollars of U.S. and Global mutual funds combined

The figure shows total assets under management in billion U.S. Dollars of all U.S. domestic, long-only equity funds and ETFs and Global long-only equity funds and ETFs during the sample period Jan.1991– Aug.2018 in the Morningstar Mutual Fund Database. Factor funds are classified as 'strategic beta' ETFs or mutual funds containing low risk, small cap, value, momentum, quality, or multi-factor in their name. For example, if a fund contains the word 'momentum' in its name it is classified as a momentum fund. Value and small-cap mutual funds are excluded from the group 'Factor funds' as they are very common across fundamental mutual funds which are not a target group of this analysis. Passive funds are classified as ETFs which are not identified as 'strategic beta' or index mutual funds.. All total assets are measured on the left axis. The right axis shows percent relative to all fund assets.



The solid purple line shows the growth of factor investing assets as a percent of total assets. Despite the exponential growth visible on figures 1.4 and 1.5, factor investing is still very small relative to the total market size. It only comprises around 3% of the total assets. However, focusing on the post-financial crisis period 2009-2018 we notice remarkable similarities between the recent growth of factor investing and the growth of passive investing in the early 1990s. As such, factor investing is still in its infancy and based on the figure has not reached its potential yet. Due to its conceptual similarity to passive investing and their common academic roots, the growth of factor investing can certainly be expected to resemble the one of passive investing over the past 30 years. This leaves considerable room for growth in factor investing and highlights the practical relevance of academic research in the field.

1.3. Thesis contributions

Based on the presented overview there are a number of open questions related to factor investing which this thesis addresses.

Market efficiency is the backbone of asset pricing and understanding its mechanisms is key in understanding factor investing. Abnormal price reaction around S&P 500 index changes has been considered as strong evidence that long-term demand for stocks is downward sloping. This notion, however, has recently been questioned because of the evidence that new additions are accompanied with a contemporaneous change in future earnings expectations. In chapter 2, we show that factor index rebalancing is an information-free event. The cumulative abnormal return from announcement to effective day is 1.07% for additions and -0.91% for deletions and around two-thirds of this effect is permanent. We find a direct relationship between the magnitude of abnormal returns and the abnormal volume coming from index funds. The documented effect results in a direct loss to index fund investors of 16.5 bps per annum. This chapter has direct implications on the mechanism through which factor-based strategies are delivered to the market. Due to them being active in nature and require regular rebalancing with relatively high turnover compared to market capitalization weighted indices, investors should be aware of the additional cost dimension which is related to it. Namely, price pressure induced by index funds engaging in identical trades at index reconstitution.

Chapter 3 relates to the most recently documented quality factor, where quality is used as a common term for accounting-based factors such as low accruals, high profitability, and low investments. High (low) quality stocks generate anomalously high (low) returns from the standpoint of prominent asset pricing models. We provide a comprehensive overview of the commonly used quality definitions and test their predictive power for stock returns. We show that quality measures predict stock returns if and only if they forecast earnings growth, and that this information is not contained in other characteristics that have been shown to drive expected returns on stocks. Our results provide empirical evidence supporting the theoretical relation between profitability, investments, and expected stock returns, proposed by Fama and French (2015), across various markets, and thereby help better understand the existence of the quality anomaly. Chapter 3 addresses one of the most fundamental questions which are still under heated debate, namely why do factor premiums exist. Related to the quality factor, it is because it successfully predicts future earnings growth and therefore is associated with higher expected return under the dividend discount model. By understanding the source of the quality premium investors can design more efficient strategies that avoid unnecessary risk or features associated with it.

In the final chapter we look at perhaps the most important question – did investors actually benefit from the positive performance of factor-based strategies. Mutual funds following factor investing strategies based on equity asset pricing anomalies, such as the small-cap, value, and momentum effects, earn significantly higher alphas than traditional actively managed mutual funds. A buy-and-hold strategy for a random factor fund yields 110 basis points per annum in excess of the return earned by the average traditional actively managed mutual fund. However, the actual returns that investors earn by investing in factor mutual funds are significantly lower because investors dynamically reallocate their funds both across factors and factor managers. Although factor funds have attracted significant fund flows over our sample period, it appears that fund flows have been driven by factor funds earning high past returns and not by the funds providing factor exposures. We argue that rather than timing factors and factor managers, investors would be better off by using a buy-and-hold strategy and selecting a multi-factor manager.

1.4 Practical implications

Next to the contributions to the academic stream of literature, this thesis has a number of important practical considerations.

A big part of the rapid growth in factor investing strategies is due to the availability of factor indices, also known as smart-beta indices. These indices possess a number of attractive characteristics such as full transparency, simple rules-based methodology, and low costs. These are all characteristics which resonate well with the passive investing philosophy. However, there is one significant difference between passive indices and factor indices – turnover. Factor indices are active in nature. As such, they require frequent rebalancing, and turnover can range between 10% to more than 100% single-counted per year. When this is compared to the turnover of around 1% per year for a typical passive index the difference becomes apparent. The relatively high turnover of factor indices magnifies the importance of trading around their rebalancing moments. This is what we investigate in Chapter 2. Our results present compelling evidence that prices of new additions (deletions) move abnormally high (low) prior to the reconstitution of the relevant indices. Namely, the cumulative abnormal return from announcement to effective day is 1.07% for additions and -0.91% for deletions. After taking turnover into account, the total costs for the end investor amounts to 16.5 basis points per annum. These costs are a direct loss to investors in public factor indices and can be seen as an additional shadow price. As such, the low-cost feature of factor indices is much less straightforward compared to the low cost of passive indices.

The solution to the effect of abnormal price movements prior to index rebalancing is not apparent. On the one hand, smart implementation techniques designed to trade in a way avoiding price increases prior to additions mitigates the problem. If index fund managers trade right after announcement day they will mitigate some of the negative impact as the biggest reaction is at the effective day due to index funds aiming to minimize tracking error. On the other hand, if all index funds do this the highest price impact will transition from the effective day to the announcement day and the added value of early trading will vanish. This is exactly what we see more recently – the highest volume is moving earlier, showing that index funds start to trade faster. However, this is where the other bottleneck lies. Unlike passive strategies where new additions are unpredictable, factor indices have widely available methodologies. By replicating the rules of the index, investors can almost perfectly predict which stocks will be bought and which stocks will be sold even before the official announcement day. This would be especially attractive for hedge funds trying to exploit inefficiencies in financial markets. Knowing that a large sum of assets will be invested in specific stocks at a specific date provides an opportunity for arbitrage profits. Our results point in a similar direction. New additions (deletions) have cumulative abnormal return of 12 (-27) basis points during the 10 days before announcement. Although statistically insignificant these results should raise a red flag to investors. By looking at the exponential growth in assets of factor funds, as shown in figure 1.4, these effects are only expected to magnify in the future.

The active nature of factor indices introduces yet another innovation in financial markets. Namely, the separation of intellectual property from fulfilment. Up until the rise of factor investing, strategies have been classified as active and passive. Active typically refer to an active mutual fund and passive – to ETFs or index funds which track a passive index, such as S&P 500. Factor indices are active in their construction as they can involve a different level of skill or intellectual property in terms of exact factor definitions, weighting schemes, and rebalancing schedules. At the same time, they are passive in implementation, as index funds purely follow the underlying index. The separation of intellectual property from implementation is associated with a number of advantages but also comes with new challenges. The main advantage is that it allows companies to focus on their strength by providing only the aspect they are good at. In line with the 'invisible hand' of Adam Smith, this ensures a more efficient distribution of wealth in the economy. On the other hand, it brings potential conflicts of interest which were non-existent until now. First, index providers do not manage the underlying assets but typically charge their clients based on the assets that are managed versus their index. As such, they have the incentive to sell infinite amounts in a single index without considering capacity constraints. Active mutual funds, for example, would typically soft close a strategy if assets grow to an amount where price impact outweighs the alpha generated by new trades. The seemingly 'infinite' capacity creates a potential of overcrowding of factor indices. The empirical results in chapter 2 provide strong evidence that this is actually the case. The additional demand is so high that it causes a permanent upward shift in the prices of new additions. Second, the separation of active index construction and passive replication defines another potential principal-agent problem. Namely, that index fund managers can influence their own benchmarks. Typically when managers trade they generate price impact and this price impact is incorporated in their net performance. On the contrary, when an index tracking managers buy new additions before the effective day, the price impact is not reflected in their net returns relative to their benchmark because the stocks are not part of this benchmark yet. Even more, stocks become an official part of the benchmark at the peak of the price increase, and managers appear to have an outperformance relative to their official benchmark despite the negative price movement they generate. To mitigate this principal-agent problem, investors in index funds might use the so-called pro-forma index as a benchmark to more precisely monitor the added value of trading during rebalancing periods. The pro-forma index assumes index changes become effective right after their announcement. Consequently, the trade-induced price impact is reflected in the total return of the pro-forma and managers would appear to underperform it after trading costs. The degree of underperformance relative to the pro-forma index is the most accurate measure of the added value of trading during index rebalancing moments.

Chapter 3 provides direct guidance to asset managers on how to define the quality factor. Unlike, other studies which aim at defining the best possible set of characteristics that deliver the highest return we provide a structural approach in the definition of the quality factor. Namely, a good quality characteristic is one that positively predicts future earnings growth. On the one hand, we show that quality measures predict stock returns if and only if they forecast earnings growth, and that this information is not contained in other characteristics that have been shown to drive expected returns on stocks. On the other hand, quality measures that are commonly used in the industry do not meet this criterium. For example, earnings based measure such as return-on-equity or return-on-assets are perhaps the most common profitability measures which are used as a signal in many quality indices such as MSCI Quality Indices and S&P Quality Indices. At the same time, we show that they predict future earnings growth negatively due to mean reversion in earnings. This effect is consistent with the study of Sloan (1996) who show that only the cash component of earnings is persistent through time. By understanding the source of the quality premium, our results go beyond providing the best definition given the historical performance. Investors can now dynamically assess if the conditions justifying the existence of the factor hold and if not adjust their definition accordingly.

In chapter 4 we look at factor investing from the point of view of asset owners. Given the strong growth in factor strategies, investors seem to understand their added value. The main recommendation of Ang, Goetzmann, and Schaefer (2009) is that an appropriate governance structure is needed for factor investing to add value in reality. Asset owners typically take their allocation decisions as follows: first they decide on the allocation across asset classes (e.g. equities, fixed-income, alternatives, etc.); then within each asset class regional splits are created; afterwards active managers are selected within each region; finally, active managers select individual stocks. The bottom-up active selection results in certain factor exposures on a total portfolio level. However, if factor exposures are just a result of bottom-up active stock selection, asset owners have no control on resulting factor exposures. Chapter 4 shows that if those factor exposures end up being in the wrong market segment (e.g. no positive factor exposure) the probability of outperforming the market on a total portfolio level is only 17%. On the other hand, if factor exposures end up being in the right segment of the market (e.g. positive exposure to four or more factors), the probability of outperforming the benchmark is 88%. Given those figures, it is beneficial for asset owners to be in control of the factor exposures of their overall portfolio. Ang, Goetzmann, and Schaefer (2009) advocate that asset owners should gain control over their total factor exposures. This message seems to have been taken well as investors started to allocate to funds explicitly targeting factor premiums, as shown in detail in figure 1.4.

Even though investors seem to learn and incorporate academic insights in their investment process the transition does not happen overnight. The fact that investors allocate to factor strategies does not mean that they have been able to benefit from them. In chapter 4 we show that despite the average mutual fund has outperformed its benchmark on a risk-adjusted basis, the average investor in this fund has underperformed it. Our evidence shows that this is happening due to poor timing of their allocation decisions. On average investors invest in factor funds after a period of good performance and withdraw after a period of poor performance. We formally test whether investors strategically allocate to factor funds and find no evidence for it. This presents a self-fulfilling prophecy. First investors gain control over asset managers on the strategic allocation to factors in order to increase their probability of success. However, instead of investing strategically they tend to time this decision, transferring it into a tactical decision. The poorly executed allocation decision might outweigh the benefits of factor allocation itself. To solve the problem investors should treat strategic decisions strategically. Namely, decide on the factor premiums they want to be exposed to in the long-term and invest accordingly. The decision needs to be a long-term strategic decision and not a tactical one. The results in this dissertation provide strong evidence that, in order to increase their probability of success, investors should allocate to multiple factors simultaneously and hold on to the decision.

1.5 Declaration of Contributions

In this section, I declare my contributions to the different studies in this thesis and acknowledge the contributions of others.

Chapter 1: I have written this chapter independently

Chapter 2: This chapter is based on the paper of Huij and Kyosev (2016). The idea of abnormal price pressure during factor index rebalancing came about during a number of discussions between me and my supervisor Joop Huij. We jointly formulated the research question and framework to empirically test this effect. I positioned the paper in the stream of literature on market efficiency and demand curves for stocks. Furthermore, I gathered the data, did the programming, performed the analysis, and wrote the current draft of the paper. A modified version of this chapter will be submitted for publication at a top finance journal.

Chapter 3: This chapter is based on the paper of Kyosev, Hanauer, Huij, and Lansdorp (2018) which is currently under Revise and Resubmit in the *Journal of Banking and Finance*. The initial version of this paper was inspired by my master thesis "Quality: Above and Beyond Size, Value, and Momentum", where I was supervised by Joop Huij and Simon Lansdorp. I brought the idea to attribute the returns of quality variables to future earnings growth which is the main research question of the current draft of the paper. I performed the majority of the data work, programming, and analysis. The writing was a joint work with my co-authors where I had a leading role in the empirical results section, data and methodology.

Chapter 4: This chapter is based on the paper Van Gelderen, Huij, and Kyosev (2019). The paper version of the chapter is published in the *Journal of Portfolio*

Management. The first part of the paper is a follow up of Van Gelderen and Huij (2014) and uses the methodology, developed by Eduard van Gelderen and Joop Huij to attribute fund styles to factor groups. I contributed to the design of the paper by adding two additional sections - the bootstrap analysis where we distinguish between manager skill and luck, and using dollar-weighted returns to compare fund returns to investor returns. Furthermore, I performed the data work, programming, and analysis of the study. The writing was a joint work with my co-authors where we contributed equally.

Chapter 2

Price Response to Factor Index Additions and Deletions*

2.1. Introduction

Flat demand curve for stocks is a key assumption in modern finance theories such as the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965) and the Arbitrage Pricing Theory of Ross (1976). These concepts are based on the idea that stocks have perfect substitutes and risk is the only determinant driving stock prices. If there is no change in the perceived riskiness of a stock, investors can trade large quantities with no significant price impact. In this paper, we document significant abnormal price movements around factor index additions and deletions and provide evidence in favor of download sloping demand curves.

As the lack of evidence for flat demand curves could cast doubts on these concepts a large body of literature is concentrated in this area. The general research framework is to identify stocks that exhibit supply shocks and examine their subsequent price reaction. The first stream of literature investigates price movements around large block sales and surprisingly document strong negative reactions (e.g. Scholes, 1972, Partch, 1985, Holthausen, Leftwich, and Mayers 1987). However, these events arguably suffer from information contamination. That is if the supply shock is caused by a flow of new information to the market then price movements are rational and reflect adjustments to their new

* This chapter is based on the paper of Huij and Kyosev (2016)

fundamental values. Large block sales are often triggered by investors having new negative information about the stock. Later studies acknowledge this weakness and look for other ways to identify information-free events.

A large stream of literature on demand curves focuses on abnormal return patterns around S&P 500 index changes. It is motivated by the fact that, as Standard and Poor's claims, this index contains no relevant information about stocks, meaning that additions and deletions are purely mechanical. As such, if markets are efficient and demand curves for stocks are flat, new additions to the index are not supposed to exhibit abnormally high returns. Harris and Gurel (1986), Shleifer (1986), Beneish and Whaley (1996), Chen, Noronha, and Singal (2004) all document the opposite – new additions are associated with high abnormal returns. These studies, however, disagree on the reason for the price movement. Harris and Gurel (1986) show that the effect is temporarily driven by compensation for providing immediate liquidity. The remaining studies find a permanent price increase consistent with long-term downward sloping demand curves, which casts serious doubt on the efficient markets hypothesis.

More recent studies question the premise that S&P 500 additions are information-free events. Denis, McConnell, Ovtchinnikov, and Yu (2003) show that newly added stocks significantly improve both their forecasted and realized earnings, suggesting that despite thought to be information-free, index additions do contain new information for stocks. Therefore, the documented abnormal inclusion returns are not evidence for downward sloping demand curves but, similar to large block sales, they reflect the mechanism of prices adjusting to their fundamental values. Some of the reasons mentioned to explain the improved fundamentals after inclusion in the S&P 500 are better monitoring by investors, higher reputation risk for firm managers causing them to put more efforts, or higher analyst coverage leading to higher information quality which lowers the risk premium related to information uncertainty demanded by investors.

In this paper, we identify a unique and novel information-free event in factor index additions and deletions. These type of indices are relatively new investment vehicles based on the insights of Fama and French (1992, 1993) that some market segments, such as high book-to-price or small capitalization stocks systematically outperform the market portfolio in the long run. This trend, also known as factor investing, quickly gains popularity in the financial industry and opens new possibilities for practitioners as well as academics.

Factor indices are characterized by two unique features. First, all stocks included in the index are already part of a broader “parent” index. As such, the critique that there is an improvement in fundamentals after including stocks in a “parent”, e.g. S&P 500, is ungrounded since all stocks of a sub-index are already part of the broad index. Consequently, there is no increased analyst coverage, management motivation, or better monitoring just because a stock is moved from one segment of S&P 500 to another. Second, the construction of factor indices is purely mechanical as it is simply based on ranking stocks on characteristics such as book-to-price, past volatility, or return-on-equity. This information is public and available to market participants so using it to put a ‘label’ on a stock should have no consequences for future stock return.

The contributions of this paper can be summarized as follows. First, by using MSCI Minimum Volatility indices we show that factor index rebalancing is a true-information free event. Additions and deletions are not associated with a significant increase in future earnings expectations. Second, we document positive (negative) and significant abnormal price reaction for newly added (deleted) stocks. The cumulative abnormal return from announcement to effective day is 1.07% (-0.91%) and around two-thirds of this effect is permanent. This evidence suggests that after a stock is added to a factor index there is a new supply-demand equilibrium achieved from a rightward shift of a downward sloping demand curve. Third, we find a direct relation between the magnitude of abnormal returns and the abnormal volume coming from index funds. Finally, we estimate the cost of transparency for public factor indices to be 16.5 bps per annum. This cost is effectively a shadow price and needs to be taken into account by investors in indices aiming to provide access to academically documented factor premiums.

The rest of the paper is organized as follows. Section II makes a detailed overview of the related literature and explanation hypotheses. Section III describes our data, index choice, and methodology. Section IV summarizes our main empirical findings. Section V presents a discussion and an alternative explanation of the results. Section VI explains the practical implication of our study and Section VII concludes.

2.2. Related literature and competing hypotheses

2.2.1. Related literature

The idea that S&P 500 index changes contain no information about the earnings of companies triggered a wave of academic research using it as a tool to examine the assumptions of CAPM and modern finance theory. In his influential study, Shleifer (1986) questions the market efficiency hypothesis by showing that a new stock inclusion to the S&P 500 index results in a 3% permanent price increase. The main hypotheses which explain this pattern are the imperfect substitutes hypothesis and the price pressure hypothesis. Shleifer attributes his results to downward sloping demand curves triggered by increased index fund trading which is in line with the former hypothesis.

In a simultaneous study, Harris and Gurel (1986) also test abnormal return and volume reactions around S&P 500 index changes. Unlike, Shleifer (1986), Harris and Gurel (1986) document that the abnormal price increase almost fully reverses within two weeks. The temporary nature of the effect provides evidence for the price pressure hypothesis which suggests that long-term demand curves for stocks might still be flat as proposed by the efficient markets hypothesis. As such, the abnormally high return immediately following the announcement of index changes serves as a compensation for passive stockholders who offer immediate liquidity to index funds, while the subsequent price reversal allows them to buy back their stock at a profit.

Beneish and Whaley (1996) analyze the effect of a methodological change in the S&P 500 composition – the decision to announce future index changes five days before they are actually implemented. Using intraday data the authors show that this change affects index tracking significantly. The previously documented 3% immediate price increase in Shleifer (1986) appears to be an unfeasible trading strategy as this is a close-to-open return reflecting market microstructure mechanisms. However, the five day pre-announcement period attracts risk arbitrageurs who buy future additions in advance with the idea to sell them at a higher price later on. This arbitrage activity is estimated to increase prices with around 2.2% before the effective day.

Chen et al. (2006) dig deeper into the negative effect of risk arbitrageurs to index investors. First, they justify five days pre-announcing window as it allows investors to prepare better for future trades. However, as index trackers are forced to keep a low tracking error, they tend to buy the new additions at the effective day, allowing arbitrageurs to perfectly anticipate the future trades. The loss of S&P 500 index investors is reported to be as large as 4 bps amounting to almost 4 billion US dollars per annum.

Chen et al. (2004) study in further detail both the additions and deletions to the S&P 500 index. They confirm the findings of Shleifer (1986) that prices of newly added stocks exhibit a permanent increase. However, they contribute to the literature by showing that there is an asymmetric effect in price responses, caused by the lack of permanent price decline for index deletions. The effect is explained with a change in investor's awareness as the number of shareholders in a given stock is largely increased after it is added to the index but it is not decreased after the stock is delisted. In contrast, in an earlier study, Goetzmann and Garry (1986) show a continuous price drop following an exclusion from the S&P 500 index, motivated with expectations for worsened quality of the future financial information, stemming from reduced analyst coverage or poorer control on accounting statements.

Denis et al. (2003) recognize the importance of this stream of literature and dig deeper into their main assumption – no underlying information change after an S&P 500 addition. They do so by analyzing the expected and realized earnings prior to and following an addition to the index. Surprisingly, the study finds that analyst earnings forecasts of newly added stocks are higher than the forecast of the benchmark companies. Furthermore, the realized earnings of new additions beat those of peer firms, indicating that operating performance improves after stocks are added to S&P 500. The authors do not elaborate on the causal relationship of whether stocks experience improved performance because they are added to the index or they are added to the index because of their improved performance (despite S&P rejecting the later). In both cases, the fact that announcement for an index change is associated with positive earnings information for the newly added firms means that S&P 500 index additions are not information-free events.

Boyer (2011) first initiates factor or style indices as academically interesting phenomena. He focuses on S&P/Barra Value and Growth indices as they are already part of the broader S&P 500 index and convey no additional information about stocks. Boyer shows that a simple relabeling of a stock from 'value' to 'growth' increases its co-movement with the index to which it is added irrespective of the change in characteristics of this stock. He attributes these movements to active style investors who want to mitigate the deviation from the relevant style benchmark.

The information content of S&P 500 index additions has opened a gap in the literature which still persists. We fill this gap by analyzing abnormal price reaction around factor index additions and deletions as proxies for information free events.

2.2.2. Competing hypotheses

Imperfect substitutes hypothesis

Classic asset pricing theories such as CAPM and APT assume that demand curves for stocks are perfectly elastic or flat. In a CAPM framework risk is the only determinant of stocks expected return and investors can buy unlimited quantities of any stock. That is if supply of a stock is scarce they will buy another stock with similar risk-return characteristics. APT assumes that investors can replicate any stock with a combination of other stocks so supply shocks have no effect on its expected return. Introducing real-life frictions in such a model might change the perception of perfect substitutes. For example, if a new stock is included in an index, there is higher demand from index trackers, motivated by maintaining lower tracking error rather than its risk-return characteristics. That is, if stock A is included in an index and stock B has exactly the same expected return, index fund investors will still prefer stock A. However, the unchanged risk-return profile gives no incentive to investors holding the stock to sell it. As such, they will require a higher return premium in order to sell the stock to passive investors which will move the equilibrium price up. This framework has been used to interpret permanent price increase around demand shocks as evidence for long-term downward sloping demand curves.

Price pressure hypothesis

The price pressure hypothesis gives an explanation of abnormal returns around index rebalancing which is in line with the efficient markets hypothesis. It assumes that if prices reflect all available information demand is perfectly elastic in the long run. However, it does not mean that short-term frictions are not possible. In this case, there is no new equilibrium price caused by index trackers. Price goes up due to market microstructure mechanisms. In the face of high unbalanced supply and demand orders, market makers face costs related to deviating from optimal inventory and finding a counterparty for the trade. To offset these costs the market maker will adequately adjust the bid-ask spread which will be reflected in the observed price. However, when the price deviates too much from its fundamental value, informed investors will trade in the opposite direction which will bring it back to the existing equilibrium level. This would mean that demand curves slope down only in the short-term while remaining flat in the long-term.

2.3. Data and methodology

2.3.1. Data

We download Morgan Stanley Capital International (MSCI) constituent data for Global markets, United States, Europe, and Emerging markets from FactSet. For each region, we download MSCI Minimum Volatility holdings as well as the relevant parent index holdings. Detailed data description can be seen in Table 2.1.

MSCI Minimum volatility indices are rebalanced twice a year, last working day of May and November at close prices and the change becomes visible on the next working day. The first rebalancing with available data on FactSet is November 2010 (May 2011 for Europe) which is when we start our analysis. This differs from the actual launching date of the index which is in 2008 for Global markets and U.S and 2009 for Europe and Emerging markets but is a reasonable assumption since major index trackers such as iShares started tracking the index in 2011. Our final sample is November 2010 – December 2015 consisting of 11 rebalancing moments. On average MSCI Minimum Volatility indices have 183 stocks with 20 new additions and 14 new deletions per rebalancing. The actual number of additions and deletions ranges between 12 and 25 for the additions and 10 and 19 for the deletions.

Table 2.1: Descriptive statistics of MSCI Minimum Volatility indices

The table shows descriptive statistics of the 4 MSCI Minimum Volatility indices used to dorm our sample. Launch date is the official launching date of the index. Start date is the date when it was first included in our sample which corresponds with the date when holdings data are available on FactSet. All stocks, additions, and deletions are the average number of all stocks, new additions, and new deletions during the 11 rebalancing moments of our sample period. Sample period is November 2010 – December 2015. Turnover is the average annual one way turnover of the index.

Index name	Parent index	Launch date	Start date	All stocks	Additions	Deletions	Turnover %
MSCI World Minimum Volatility (USD) Index	MSCI World	Apr-08	Nov-10	246	29	24	20
MSCI USA Minimum Volatility (USD) Index	MSCI USA	Jun-08	Nov-10	140	14	10	20
MSCI Europe Minimum volatility (USD) Index	MSCI Europe	Nov-09	May-11	121	12	8	20
MSCI EM Minimum Volatility (USD) Index	MSCI Emerging Markets	Dec-09	Nov-10	224	25	15	20
average				183	20	14	20

The annual single counted turnover is 20% which matches the announced turnover by MSCI.

Our return and shares outstanding data are downloaded from Interactive Data Exshare. If not available we use MSCI returns series, and where this is also not available - S&P/IFC. Daily returns include dividends, stock splits and other capital adjustments and are denominated in US dollars. Free float-adjusted market capitalization data are obtained from FTSE and S&P/IFC and. U.S. dollar-denominated price and trading volume per share data are gathered from FactSet. Volume is measured in U.S. dollar per share traded per day at all exchanges where the stock is listed with available data on FactSet. We then multiply it by the number of shares outstanding to calculate our total trading volume variable. Analyst earnings forecast data are gathered from the Institutional Brokers' Estimate System (IBES). We use the median forecast for end of fiscal year one (FY1) and fiscal year 2 (FY2).

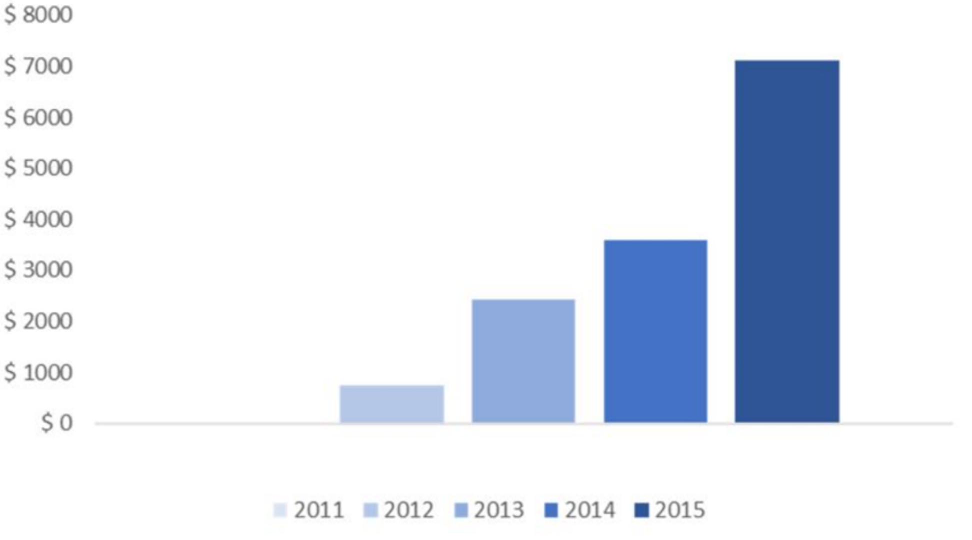
MSCI Factor Indices.

MSCI has introduced a new family of indices aiming to provide exposure to academically documented factor premiums. The two most popular and long-standing indices are MSCI Value Weighted Index and MSCI Minimum Volatility index. The former uses an approach of weighting all constituent stocks in the parent index according to valuation variables such as book-to-price. This makes it unsuitable to investigate price reaction around new additions as they overlap with the additions to the parent index. On the other hand, MSCI Minimum Volatility index family is one that aims to provide access to the low volatility factor (Black, 1972, Ang et.al, 2006, Blitz and Van Vliet, 2007) by investing in a subset of stocks with lower risk profile within its parent index. This ensures that new additions do not coincide with new additions to the parent index but are rather relabeling of existing stocks.

MSCI Minimum Volatility index uses the Barra Open Optimizer to create a minimum variance portfolio conditional on a predefined set of constraints (MSCI Minimum Volatility Indices Methodology, 2012). The resulting portfolio is a subset of the relevant parent index e.g. MSCI World index. The index is rebalanced semi-annually coinciding with the parent index rebalancing. Changes in the index are effective as of the close of the last working day in May and November which makes them visible the first working day of the next month. According to MSCI, changes are announced nine trading days before they actually take place. Turnover is limited to 20% per year single counted as it is split between new inclusions and reweighting existing stocks in the index. Figure 2.1. shows the growth in assets of MSCI Minimum Volatility index by focusing on the assets of a popular ETF which track it.

Figure 2.1: Total Net Assets of iShares Edge MSCI Min Vol USA ETF

The figure shows the total net assets per year end of iShares Edge MSCI Min Vol USA ETF which tracks MSCI USA Minimum Volatility index. Scale is in million US dollars.



2.3.2. Methodology

The first step in our approach is to identify new additions and new deletions. A stock is considered newly added (deleted) the first day when it is in (out of) the portfolio. This day we identify as the effective day (ED). Since MSCI adds stocks at close prices a stock is effectively in the portfolio at market open at ED, meaning that if index trackers want to have the stock at ED they need to buy it at ED-1. Announcement day (AD) is nine business days before stocks are added (deleted) so AD = ED-9.

We follow these steps for MSCI Minimum Volatility indices as well as their relevant parent indices. We exclude stocks which are simultaneously added to the factor index and the parent index. This step has two important consequences. First, we control for the "S&P 500" inclusion effect. Previous literature has shown strong and significant price reaction around S&P 500 additions as Chakrabarti et al. (2005) show that the effect holds for other benchmark indices such as MSCI World or MSCI USA index. Since MSCI Minimum Volatility indices are rebalanced at the same times as their parent indices some stocks enter both indices simultaneously. As such, it might be that the observed price reaction for the overlapping stocks is not due to addition to the factor index but due to addition to the parent index which is an already documented effect. Removing these stocks from our sample allows us to investigate the pure effect of factor index additions and deletions. This is a conservative choice and biases our results downwards. Second, we exclude index changes due to corporate actions. If a stock is added (excluded) to a factor index due to corporate events such as spin-off or acquisition it will (not) be seen also in the parent index at the same time. Excluding parent index changes will remove corporate action motivated index changes from our sample.

Our main analysis follows a standard event study methodology. The abnormal return of a stock i at day t (AR_{it}) is calculated as the return of stock i in excess of the return of the factor index it is added to (excluded from). We use the factor index as the appropriate benchmark to control for the low beta characteristics of the low risk stocks targeted by minimum volatility indices. This is also the relevant benchmark for investors in factor indices. Cumulative abnormal return (CAR) of stock i from day t-n to day t is calculated as the sum the abnormal returns of stock i from day t-n to day t ($CAR_{i,t-n:t} = \sum_{t-n}^{t} AR_i$). Average abnormal return at day t (AAR_t) is the average of the abnormal returns of all new additions (deletions) at day t ($AAR_t = \frac{1}{N}\sum_i AR_{it}$, where N is the number of additions or deletions). As a robustness check we also calculate abnormal returns using a market model. We only include trading days removing weekends and public holidays. Public holidays we define as days with no trades in any stocks of the parent index. In our global markets analysis we exclude U.S. public holidays as in these days trading volume is abnormally low and distorts the market volume ratios.

In our main sample we include additions and deletions from the four regional MSCI Minimum Volatility indices – United States, Global markets, Europe, and Emerging markets. The abnormal return of every stock is calculated relative to the index it is added to (deleted from). So if at day t we have two additions – stock A and stock B. Stock A is added to MSCI USA Minimum Volatility index and stock B is added to MSCI World Minimum Volatility index the average abnormal return (AAR) of our sample at month t would be the average of the excess return of stock A over MSCI USA Minimum Volatility index and the excess return of stock B over MSCI World Minimum Volatility index.

The abnormal volume estimation methodology follows the one used in Harris and Gurel (1986). We calculate the ratio of trading volume of a stock divided by its normal trading volume, corrected by the trading volume of the market divided by the market's normal trading volume. The average abnormal volume (AAV) for all additions deletions is

$$AAV_t = \frac{1}{N}\sum_i \left(\frac{V_{it}}{V_{mt}} . \frac{V_m}{V_i}\right) \tag{2.1}$$

Where V_{it} is the dollar traded amount of stock i at day t, V_{mt} is the dollar traded amount of all stocks in the parent index at day t, V_i is the 40 day average trading volume of stock i from AD-50 to AD-10 where AD is the announcement day. AD-10 (ten days before the announcement day) is the first day of our event window, V_m is the average trading volume of all stocks in the parent index from AD-50 to AD-10. Our final sample formation follows the same steps as the sample for abnormal returns.

We calculate the earnings expectation changes in the spirit of Denis et al. (2003). Use the median analyst forecast denominated in U.S dollars. The change in forecast of stock i (ΔF_{it}) is calculated as the difference between the median analyst forecast 10 days after the effective day and the median analyst forecast 10 days before the effective day (one day before the announcement day). The average change in earnings forecast for all additions (deletions)

$$AF_t = \frac{1}{N}\sum_i (F_{it} - F_{it-20}) \tag{2.2}$$

We also calculate the average change in forecast scaled by price in order to correct for structural differences between earnings levels across countries using the following formula

$$AFP_t = \frac{1}{N}\sum_i \left(\frac{F_{it} - F_{it-20}}{P_{it}}\right) \tag{2.3}$$

We then calculate the change of earnings forecast for all stocks in the relevant factor index as the average change of earnings forecast of all constituent stocks. We use median earnings forecast for the current fiscal year end in the May rebalancing and median forecast for the end of the following fiscal year end in the November rebalancing. The reason for using fiscal year two forecast is that 10 days after the November additions is 12 days before the end of the current fiscal year end when the realized earnings are known with high certainty so expectations are less relevant.

After we have calculated the ratios we test for a difference in means between the earnings forecast change of new additions (deletions) and the market earnings forecast change.

$$t = \frac{AF_t - AFM_t}{\sqrt{\frac{s^2_{AF_t}}{N_{AF_t}} + \frac{s^2_{AFM_t}}{N_{AFM_t}}}}$$

Which has distribution T(m) with

$$m = \frac{\left(\frac{s^2_{AF_t}}{N_{AF_t}} + \frac{s^2_{AFM_t}}{N_{AFM_t}}\right)^2}{\frac{\left(\frac{s^2_{AF_t}}{N_{AF_t}}\right)^2}{N_{AF_t - 1}} + \frac{\left(\frac{s^2_{AFM_t}}{N_{AFM_t}}\right)^2}{N_{AFM_t - 1}}} \tag{2.4}$$

Where $s^2_{AF_t}$ is the variance of earnings forecast changes of all additions (deletions), $s^2_{AFM_t}$ is the variance of earnings forecast changes of all additions (deletions). N_{AF_t} and N_{AFM_t} are the number of observations in the additions (deletions) sample and all stocks in the factor index.

Finally, we run a regression of abnormal return on abnormal volume

$$AR_{i,ED-1} = a + b.AV_{i,ED-1,t} + \varepsilon_{i,ED-1} \tag{2.5}$$

Where $AR_{i,ED-1}$ and $AV_{i,ED-1,t}$ are the abnormal return and abnormal volume of stock i the last day before the effective day.

2.4. Empirical results

In Table 2.2 we show the main results of an event study surrounding additions in MSCI Minimum Volatility indices (the index). We examine both short- and long-term price reaction by using alternative event windows. The period of focus is the nine-day period between the announcement day and the effective day (AD : ED) as this is where we expect the prices to move abnormally. Panel A shows the results for newly added firms in the index. The cumulative abnormal return from AD to ED is 1.07% which is positive and highly significant (t-stat of 7.16). For 62% of the additions, CAR has been positive during this period. 0.63% out of the 1.07% is gained only in the day preceding the effective day (ED-1) showing that the effect is largely driven by the shift in demand caused by index funds. 0.31% of the cumulative abnormal return is offset in the five days following the effective day (ED : ED+5) but the price seems to stabilize at this level as it remains intact in the following 10 days ($CAR_{ED:ED+15}$ = -0.34% which is almost equal to the -0.31% from ED to ED+5). We do not extend the post addition event windows further as results might be contaminated with stock specific information.

These results suggest that 32% (0.34% out of 1.07%) of the abnormal price reaction is temporary and 68% is permanent. The high permanent increase in price is consistent with the long-term download sloping demand curve documented by Shleifer (1986). The temporary increase can be attributed to a liquidity premium charged by stock owners for rebalancing their portfolio or arbitrage activity. A distinctive feature of factor indices is that they are fully transparent. To construct them a publically known algorithm is used meaning that informed investors can perfectly anticipate the new additions (by replicating the index) even before the announcement day. Our results, however, show that this is not done as CAR in the 10 days before the announcement day is only 0.12% and is not statistically different from zero (t-stat of 0.69).

We continue the analysis with abnormal volume estimation. Our approach corrects for both stock and market normal volume levels so the expected value in a 'normal' day is 1. Panel B shows that the average trading volume of new additions between the announcement and the effective day is 30% higher than normal which is statistically significant (t-stat = 3.81). Consistent with the abnormal return analysis the highest volume is observed in the day

Table 2.2: Abnormal return and abnormal volume for new factor index additions

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The table shows event study results of abnormal returns and abnormal volume surrounding MSCI Minimum Volatility index additions (factor index). The factor index is a combination of MSCI USA Minimum Volatility (USD) index, MSCI World Minimum Volatility (USD) index, MSCI Europe Minimum Volatility (USD) index, and MSCI Emerging Markets Minimum Volatility (USD) index. Abnormal return is calculated as the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. For example if a stocks is added to MSCI USA Minimum Volatility index abnormal return is calculated over the average MSCI USA Minimum Volatility index, if it is added to MSCI Europe Minimum Volatility index, the abnormal return is calculated over MSCI Europe Minimum Volatility index. The abnormal returns of all new additions to the four indices are then pooled together to form the final sample. Abnormal volume is calculated as in equation 5. It requires a minimum of 10 observations for a stock to be included. Normal trading volume has a value of 1 and 1.30 means that the volume at the specific day is 30% higher than the normal trading volume. The final sample is formed in line with the abnormal return sample as the normal volume estimation is relative to the relevant region. CAR is cumulative abnormal return, AAR is average abnormal return, measured in percent, AV is average volume, $AV_t = \frac{1}{N}\sum_i \left(\frac{V_{it}}{V_{mt}} . \frac{V_m}{V_i}\right)$, AD-10:AD is 10 days prior the announcement day to the announcement day, AD:ED is the 9 business day from announcement day to effective day, ED-1 is 1 day prior to the effective day, ED:ED+5 is effective day to 5 days after the effective day, ED:ED+15 is effective day to 15 days after the effective day.

	AD-10 : AD	AD : ED	ED-1	ED : ED+5	ED : ED+15
		Panel A: Abnormal returns			
CAR	0.12	1.07	0.63	-0.31	-0.34
AAR	0.01	0.12	0.64	-0.07	-0.03
st. dev	0.47	0.46	2.01	0.73	0.36
t-stat	0.69	7.16	8.55	-2.73	-2.03
% > 0	0.54	0.62	0.63	0.44	0.46
N	731	731	714	731	731
		Panel B: Abnormal volume			
AV	1.07	1.30	1.74	1.16	1.15
st. dev	0.55	2.15	2.94	0.76	0.74
t-stat	3.33	3.81	6.82	5.74	5.53
% >1	0.45	0.58	0.67	0.53	0.54
N	730	730	727	730	730

prior to ED as it is 74% higher than expected. The trading volume then slowly normalized to an average of 1.15 during the three weeks after the addition. The fact that trading volume remains abnormally high relative to pre-addition levels is consistent with the permanent price increase caused by a structural shift in demand. The small difference in the number of observations is attributable to return or volume data availability.

Figure 2.2 shows the cumulative abnormal return and abnormal volume patterns on a daily basis. The trading volume starts to increase shortly after the announcement day, then lowers again, and reaches its maximum at ED-1. This pattern can be explained by arbitrageurs taking their positions right after announcement and index trackers needing to wait until the last moment to maintain low tracking error. Arbitrageurs then unwind their positions in the days after the addition takes place which justifies the sharp price drop right after the effective day. Afterwards, the price seems to stabilize.

In table 2.3 we show that the opposite conclusions hold for index deletions. CAR from AD to ED-1 is -0.91% as 57 percentage points are lost in the final day before deletion. 64% of all deletions have a negative return in the day prior to the effective day. Approximately half of the price loss (0.49% out of 0.91%) is gained back within three weeks after deletion. Compared to additions here we see a stronger price reversal after the effective day which is partly consistent with the asymmetric S&P 500 effect documented by Chen et. al (2004). Trading volume shows similar patterns like the ones for additions. It is equal to exactly 1.00 during the ten days prior announcement and then increases, peaking at the day prior to deletion at a level 46% higher than normal. It then normalizes back to 1.01 on average in the three weeks after the deletion.

Figure 2.3 shows virtually the opposite return and volume patterns to the ones of index additions. Due to short sales constraints, we do not see a very high trading volume after the announcement day. However, prices continuously drop in anticipation of the forthcoming excess supply coming from index trackers. Trading volume peaks at ED-1 and within the next two days stabilizes back to normal levels.

Figure 2.2: Cumulative abnormal return and abnormal volume around factor index rebalancing

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The cumulative abnormal return and abnormal volume surrounding MSCI Minimum Volatility index (factor index) additions and deletions. The factor index is a combination of MSCI USA Minimum Volatility (USD) index, MSCI World Minimum Volatility (USD) index, MSCI Europe Minimum Volatility (USD) index, and MSCI Emerging Markets Minimum Volatility (USD) index. Cumulative abnormal return is calculated as the sum of the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. For example, if a stocks is added to MSCI USA Minimum Volatility index abnormal return is calculated over the average MSCI USA Minimum Volatility index, if it is added to MSCI Europe Minimum Volatility index, the abnormal return is calculated over MSCI Europe Minimum Volatility index. The abnormal returns of all new additions to the four indices are then pooled together to form the final sample. Cumulative return from AD-10 to ED+15 is the sum of the abnormal returns from AD-10 to ED+15. Abnormal volume is calculated as in equation 5 and then 1 is subtracted from it. It requires a minimum of 10 observations for a stock to be included. Normal trading volume has a value of 0 and 0.30 means that the volume at the specific day is 30% higher than the normal trading volume. The final sample is formed in line with the abnormal return sample as the normal volume estimation is relative to the relevant region. AD-10 is 10 days prior the announcement, AD is the announcement day, ED-1 is 1 day prior to the effective day, ED+5 is 5 days after the effective day, ED+15 is 15 days after the effective day. The AD:ED-1 window includes 9 business days during which new additions are publicly available.

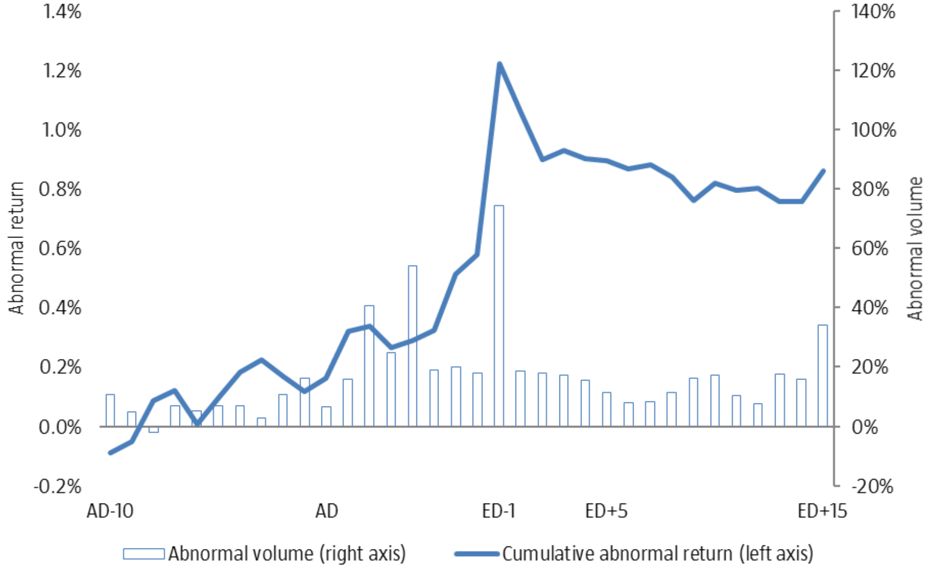


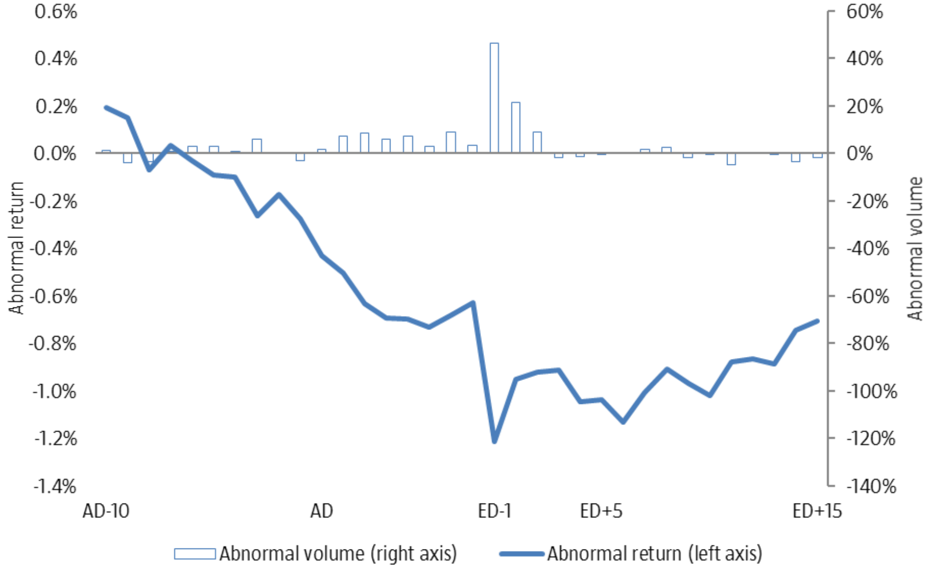
Table 2.3: Abnormal return and abnormal volume for new factor index deletions

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The table shows event study results of abnormal returns and abnormal volume surrounding MSCI Minimum Volatility index deletions (factor index). The factor index is a combination of MSCI USA Minimum Volatility (USD) index, MSCI World Minimum Volatility (USD) index, MSCI Europe Minimum Volatility (USD) index, and MSCI Emerging Markets Minimum Volatility (USD) index. Abnormal return is calculated as the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. For example if a stocks is added to MSCI USA Minimum Volatility index abnormal return is calculated over the average MSCI USA Minimum Volatility index, if it is added to MSCI Europe Minimum Volatility index, the abnormal return is calculated over MSCI Europe Minimum Volatility index. The abnormal returns of all new additions to the four indices are then pooled together to form the final sample. Abnormal volume is calculated as in equation 5. It requires a minimum of 10 observations for a stock to be included. Normal trading volume has a value of 1 and 1.30 means that the volume at the specific day is 30% higher than the normal trading volume. The final sample is formed in line with the abnormal return sample as the normal volume estimation is relative to the relevant region. CAR is cumulative abnormal return, AAR is average abnormal return measured in percent, AV is average volume, based on the formula $\boldsymbol{AV_t} = \frac{1}{N}\sum_i \left(\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}\right)$, AD-10:AD is 10 days prior the announcement day to the announcement day, AD:ED is the 9 business days from announcement day to effective day, ED-1 is 1 day prior to the effective day, ED:ED+5 is effective day to 5 days after the effective day, ED:ED+15 is effective day to 15 days after the effective day.

	AD-10 : AD	AD : ED	ED-1	ED : ED+5	ED : ED+15
			Panel A: Abnormal returns		
CAR	-0.27	-0.91	-0.57	0.17	0.49
AAR	-0.03	-0.11	-0.59	0.03	0.04
st. dev	0.62	0.59	2.35	0.96	0.47
t-stat	-1.11	-4.25	-5.67	0.82	1.75
% positive	0.47	0.43	0.36	0.54	0.55
N	527	528	517	527	527
			Panel B: Abnormal volume		
AV	1.00	1.10	1.46	1.05	1.01
st. dev	0.48	0.64	1.32	0.74	0.50
t-stat	0.08	3.68	8.01	1.59	0.63
% >1	0.41	0.45	0.60	0.40	0.40
N	526	526	526	526	526

Figure 2.3: Cumulative abnormal return and abnormal volume around factor index rebalancing

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The cumulative abnormal return and abnormal volume surrounding MSCI Minimum Volatility index (factor index) additions and deletions. The factor index is a combination of MSCI USA Minimum Volatility (USD) index, MSCI World Minimum Volatility (USD) index, MSCI Europe Minimum Volatility (USD) index, and MSCI Emerging Markets Minimum Volatility (USD) index. Cumulative abnormal return is calculated as sum of the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. For example if a stocks is added to MSCI USA Minimum Volatility index abnormal return is calculated over the average MSCI USA Minimum Volatility index, if it is added to MSCI Europe Minimum Volatility index, the abnormal return is calculated over MSCI Europe Minimum Volatility index. The abnormal returns of all new additions to the four indices are then pooled together to form the final sample. Cumulative return from AD-10 to ED+15 is the sum of the abnormal returns from AD-10 to ED+15. Abnormal volume is calculated as in equation 5 and then 1 is subtracted from it. It requires a minimum of 10 observations for a stock to be included. Normal trading volume has a value of 0 and 0.30 means that the volume at the specific day is 30% higher than the normal trading volume. The final sample is formed in line with the abnormal return sample as the normal volume estimation is relative to the relevant region. AD-10 is 10 days prior the announcement, AD is the announcement day, ED-1 is 1 day prior to the effective day, ED+5 is 5 days after the effective day, ED+15 is 15 days after the effective day. The AD:ED-1 window includes 9 business days during which new deletions are publicly available.



2.4.1. Result interpretation

In this section, we conduct further tests to differentiate better between competing explanations of the observed effect.

1. Information content in factor index changes

First, we address the information contamination hypothesis which is the main criticism of the literature focusing on S&P 500 additions.

In the spirit of Denis et. al (2003) we use a number of alternative methodologies to show the change in expectations for the future earnings of additions and deletions to the index. Panel A of Table 2.4 presents the frequency of earnings forecast changes. In this analysis, we should not only focus on the number of positive or negative forecast changes of additions and deletions but we should compare them to the frequency of changes in the relevant benchmark which, as in our event study analysis, is all constituent stocks in the factor index. During our sample period 47.1% of the forecasts are revised downwards, 36.6% upwards and 16.3% exhibit no change. This is consistent with previous studies showing the analysts are more likely to revise their estimates downwards with the approach of fiscal year end. New additions have earnings forecast frequencies almost exactly equal to those in the benchmark (47.2%, 37.3%, and15.5% respectively) meaning that the higher abnormal returns cannot be attributed to a higher likelihood of earnings forecast increase. Deletions do have a slightly higher probability of a downward revision (52.3% compared to 47.1% in the benchmark).

The equal probability of earnings forecast change in newly added firms and the benchmark does not fully mean that the anomalous returns of those stocks cannot be attributed to change in the perceived fundamentals of the companies. It could be that the number of forecast changes is the same but the magnitude of new additions and deletions is much stronger. In Panel B we test for a difference in the magnitude of earnings forecast changes. We see that the earnings forecast of additions, deletions, and the benchmark have changed with 0.02, 0.01, and 0.06 U.S. dollars per share respectively. This confirms the previous conclusion that the positive price change of additions cannot be attributed to change in fundamentals. Deletions do exhibit worse forecasts but further tests for the significance of the difference between deletions and benchmark means show that it is not statistically significant (t-stat of -1.16).

Table 2.4: Change in analyst earnings forecast for new additions and deletions to the factor index

Analyst earnings forecast change is calculated as the median analyst earnings forecast 10 days after the effective day minus the median analyst earnings forecast 10 days before the effective day (1 day before the announcement day). Current and following year median analyst earnings forecast is downloaded from IBES. The frequency of changes is the percentage of positive, negative and zero changes out of the total group which can be additions, deletions, or the factor index. Mean change in earnings forecast is measured in U.S. dollars per share, mean change in forecast standardized by price is measured as the change in eps forecast as percentage of price per share. Mean diff additions and deletions measures whether the number of additions and deletions is significantly different from the relevant number in the factor index. The sample consists of all new additions and deletion to MSCI Minimum Volatility index (factor index) during the period November 2010 – December 2015 including a total of 11 rebalancing moments. The factor index is a combination of MSCI USA Minimum Volatility (USD) index, MSCI World Minimum Volatility (USD) index, MSCI Europe Minimum Volatility (USD) index, and MSCI Emerging Markets Minimum Volatility (USD) index.

	Additions	Deletions	Index	mean diff additions	mean diff deletions
Panel A: Frequency of eps forecast changes					
negative	47.2%	52.3%	47.1%		
zero	15.5%	14.1%	16.3%		
positive	37.3%	33.5%	36.6%		
Panel B: Mean eps forecast change					
mean	0.02	0.01	0.06	-0.04	-0.06
st. dev	0.52	0.68	3.15		
t-stat	1.08	0.28	1.72	-1.02	-1.16
N	716	516	7088		
Panel C: Mean eps forecast change standardized by price					
mean	-0.03%	-0.07%	-0.02%	-0.01%	-0.05%
st. dev	0.41%	2.72%	0.44%		
t-stat	-1.92	-0.57	-4.48	-0.37	-0.38
N	716	516	7088		

Our sample of firms contains stocks from different regions that could have structurally different earnings per share levels. Therefore, in Panel C we scale earnings changes by price in U.S dollars to look at the percentage changes. The results still indicate no significant difference between earnings forecast changes of factor index additions and deletions from the benchmark. With these results we present strong evidence that factor index rebalancing is information-free event of supply shocks. This allows us to overcome the weaknesses of previous literature, focused on S&P 500 additions, and propose a novel framework for testing demand curves for stocks.

2. Volume hypothesis

Knowing that the anomalous return patterns around index reshuffles are not attributable to new information flowing to the market we can focus on trading volume as an alternative explanation. We then regress abnormal returns on our abnormal volume measure. The low tracking error requirements, as well as the results of our abnormal volume and returns analysis, suggest that index funds seem to include new stocks in the final day before the effective day. As such, the abnormal volume on that day can serve as a measure for index fund trading. If the permanent increase in prices is due to an exogenous shift in demand coming from index funds then the relationship between abnormal returns and abnormal volume should be in line with the side of the trade coming from index funds – positive for index additions and negative for index deletions.

Table 2.5 confirms this notion. The slope coefficient of abnormal volume is positive and significant meaning that their demand does affect stock prices. The opposite holds for index deletions as the coefficient is negative and highly significant. That is the high trading volume of index deletions come from the shock in supply coming from index trackers which puts negative pressure on prices. As index trackers step out of the stock the demand curve shifts left and prices stabilize at a lower level.

The specifications of Regression 3 and Regression 4 in Table 2.5 address possible alternative explanations of the observed effect. For instance, can it be attributed to other firm characteristics such as size, forward earnings valuations, and profitability. In both cases, abnormal volume is still significantly related to abnormal returns, 0.10 (t-stat of 3.24) and -0.27 (t-stat of 3.38) for additions and deletions respectively. This reassures that the abnormal price reaction is really driven by index fund demand. However, firm size is also significantly related to abnormal returns at rebalancing moments meaning that

Table 2.5: Cross-sectional regression of abnormal return on abnormal volume at the day of index changes (ED-1)

The sample consists of abnormal return and abnormal volume of all new additions and deletion to MSCI Minimum Volatility index (factor index) one day before the effective day during the period November 2010 – December 2015 including a total of 11 rebalancing moments. The factor index is a combination of MSCI USA Minimum Volatility (USD) index, MSCI World Minimum Volatility (USD) index, MSCI Europe Minimum Volatility (USD) index, and MSCI Emerging Markets Minimum Volatility (USD) index. Abnormal return is calculated as the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. For example if a stocks is added to MSCI USA Minimum Volatility index abnormal return is calculated over the average MSCI USA Minimum Volatility index, if it is added to MSCI Europe Minimum Volatility index, the abnormal return is calculated over MSCI Europe Minimum Volatility index. The abnormal returns of all new additions to the four indices are then pooled together to form the final sample. Abnormal volume is calculated as in equation 5 and then 1 is subtracted from it. It requires a minimum of 10 observations for a stock to be included. Normal trading volume has a value of 0 and 0.30 means that the volume at the specific day is 30% higher than the normal trading volume. The final sample is formed in line with the abnormal return sample as the normal volume estimation is relative to the relevant region. Control variables are the natural logarithm of market capitalization, median earnings forecast for fiscal year one scaled by price, and return on equity.

	Additions		Deletions	
	Regression 1	Regression 2	Regression 3	Regression 4
intercept	0.50	2.71	0.04	-2.06
t-stat	5.78	4.69	0.25	-2.83
abnormal volume	0.08	0.10	-0.42	-0.27
t-stat	3.32	3.24	-5.59	-3.38
ln(mcap)		-0.25		0.20
t-stat		-3.94		2.57
eps forecast to price		0.11		2.18
t-stat		0.17		4.29
return on equity		-0.01		-0.09
t-stat		-0.65		-0.65
R-sq	0.01	0.04	0.06	0.08

part of the effect comes through a liquidity channel. Abnormal returns of additions are stronger for smaller stocks which are usually less liquid. As such the high additional demand of index trackers has a bigger impact on stock prices. The opposite is observed for index deletions – abnormal returns are negatively related to firm size. Given that short sale constraints are smaller for larger firms our results suggest that part of the abnormal negative returns of deletions are due to short sale pressure coming from hedge funds.

2.4.2. Practical implications.

The results documented in this paper have strong practical considerations for index funds investors. They are the ones who ultimately bear the cost associated with price changes preceding index additions and deletions. For instance, Chen et al (2006) estimate that the dollar losses to investors in indices tracking S&P 500 is 4 bps per year which translates to an annual loss of almost 4 billion U.S. dollars. To calculate the loss to factor fund investors we multiply index turnover due to index changes by the cumulative abnormal return between announcement and effective days.

$$Performance\ drag = Turnover_{additions}\ x\ CAR_{additions} + Turnover_{deletions}\ x(-CAR_{deletions})$$

Table 2.6 presents the results for the four minimum volatility indices that we use – MSCI USA Minimum Volatility (USD) index (U.S.), MSCI World Minimum Volatility (USD) index (Global), MSCI Europe Minimum Volatility (USD) index (Europe), and MSCI Emerging Markets Minimum Volatility (USD) index (EM) . On average new additions represent 9.6% of the portfolio and new deletions 6.8%. This translates to an average performance drag of 16.5 bps which is the price investors pay to invest in public factor indices.

The CAR used for the estimation is from the announcement day to the close the day before the changes take place. Therefore, some index trackers are able to buy (sell) additions (deletion) before the close price which will lower the estimated performance drag. On the other hand, the 16.5 bps can be biased downwards as the actual number might be higher due to a number of reasons. First, new additions and new deletions correspond to less than half of the total turnover of the index. The remaining turnover comes from weight changes of existing stocks which are also announced in advance. This makes them attractive for arbitrageurs as well as forces index trackers to readjust their portfolio accordingly which could generates price impact even if it is lower than the one for added and excluded stocks. Second, we exclude stocks which are added (deleted) from the parent index to avoid overlap with the already documented 'S&P 500' effect. The stocks which are added to (deleted from) the parent index are expected to have much higher (lower) abnormal returns as they are bought (sold) by index trackers following the parent index and its multiple sub-indices.

Table 2.6: Percentage losses to investors in MSCI Minimum Volatility indices due to price reaction before additions and deletions announcement.

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The table shows turnover, cumulative abnormal return, and performance drag of MSCI Minimum Volatility index additions and deletions. Turnover is the sum of the weight of all additions or deletions in the relevant index. CAR (AD:ED-1) is the cumulative abnormal return from the announcement day to one day before the effective day. Performance drag is calculated by multiplying the turnover and CAR of additions and adding the negative of the product of turnover and CAR of deletions. The four indices used are MSCI USA Minimum Volatility (USD) index (U.S.), MSCI World Minimum Volatility (USD) index (Global), MSCI Europe Minimum Volatility (USD) index (Europe), and MSCI Emerging Markets Minimum Volatility (USD) index (EM). Abnormal return is calculated as the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. Performance drag is measured in basis points.

	Turnover		CAR (AD:ED-1)		Performance
	additions	deletions	additions	deletions	drag
U.S.	7.3	6.2	0.6	-0.5	7.4
Europe	7.8	6.2	0.9	-1.6	16.4
Global	11.5	9.2	1.2	-1.0	22.1
EM	11.6	5.7	1.4	-0.8	20.2
average	9.6	6.8	1.0	-1.0	16.5

Finally, even though we don't find evidence for it, it is possible that arbitrageurs replicate the index algorithm and start trading well before the index changes are announced. These points have significant implications for the pricing of publically available investment vehicles as return loss due to publically announced trades can be seen as a shadow fee.

2.5. Conclusion

We propose a new information free event of supply shocks in the face of factor index rebalancing. Previous literature has been concentrated around large block sales and changes in S&P 500 index constituents but these events have been shown to contain information about the future earnings potential of companies. We show that there is no link between factor index additions and deletions and improved earnings expectations. This allows us to attribute the documented abnormal returns to a shift an exogenous shift in demand. The abnormal return for new additions (deletions) between announcement and effective day is 1.07% (-0.91%) as 0.73 (-0.42) percentage points of it persist after 3 weeks following the effective day. Similar pattern is seen for abnormal volume as at the effective day it is 74% (46) for additions (deletions). We document a direct relationship between abnormal returns and our proxy for the trading coming from index funds who seem to wait until the last day before adjusting their portfolio. Finally, we calculate the price of transparency for public factor indices to be 16.5 bps per annum which is a direct loss to index fund investors.

Appendix

Table 2.7: Market model abnormal return for new factor index additions and deletions

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The table shows event study results of abnormal returns surrounding MSCI Minimum Volatility index additions and deletions. The four indices used are MSCI USA Minimum Volatility (USD) index (U.S.), MSCI World Minimum Volatility (USD) index (Global), MSCI Europe Minimum Volatility (USD) index (Europe), and MSCI Emerging Markets Minimum Volatility (USD) index (EM). Abnormal return is calculated as the total USD return of the stocks in excess of the expected return based on the following equation $AR_{ti} = TR_{it} - [b_i.(R_{m,t} - R_f) + R_{ft}]$, where b_i is calculated based on the 250 trading days ending 1 days before the announcement day using the following equation: $TR_t - R_f = a + b.(R_{m,t} - R_f) + \varepsilon_t$ where TR_t is the total return of stock i at month t, R_f is the U.S. risk-free rate as provided on the Kenneth French website, $R_{m,t}$ is the relevant market portfolio (United States, Global developed markets, Europe, and Emerging markets). AAR is average abnormal return, AV is average volume, AD-10:AD is 10 days prior the announcement day to the announcement day, AD:ED is announcement day to effective day, ED-1 is 1 day prior to the effective day, ED:ED+5 is effective day to 5 days after the effective day, ED:ED+15 is effective day to 15 days after the effective day.

	AD-10 : AD	AD : ED	ED-1	ED : ED+5	ED : ED+15
			Panel A: Additions		
CAR	0.47	1.03	0.50	-0.37	-0.21
AAR	0.05	0.11	0.50	-0.07	-0.01
St. dev	0.42	0.45	1.96	0.65	0.35
t-stat	2.93	6.72	6.81	-3.05	-1.05
% > 0	0.59	0.64	0.62	0.43	0.47
N	700	700	700	700	700
			Panel B: Deletions		
CAR	0.59	-0.73	-0.63	-0.01	0.71
AAR	0.06	-0.09	-0.63	0.00	0.05
St. dev	0.57	0.59	2.29	0.89	0.43
t-stat	2.30	-3.30	-6.23	-0.08	2.47
% > 0	0.56	0.44	0.34	0.52	0.54
N	508	509	509	508	508

Table 2.8: Abnormal return and abnormal volume for new additions and deletions to the individual MSCI Minimum Volatility indices

The sample period is November 2010 – December 2015 including a total of 11 rebalancing moments. The table shows event study results of abnormal returns and abnormal volume surrounding MSCI Minimum Volatility index additions and deletions. The four indices used are MSCI USA Minimum Volatility (USD) index (U.S.), MSCI World Minimum Volatility (USD) index (Global), MSCI Europe Minimum Volatility (USD) index (Europe), and MSCI Emerging Markets Minimum Volatility (USD) index (EM). Abnormal return is calculated as the total USD return of the stocks in excess of the average total USD return of all stocks in the relevant factor index. For example, if a stocks is added to MSCI USA Minimum Volatility index abnormal return is calculated over the average MSCI USA Minimum Volatility index, if it is added to MSCI Europe Minimum Volatility index, the abnormal return is calculated over MSCI Europe Minimum Volatility index. Abnormal volume is calculated as in equation 5. It requires a minimum of 10 observations for a stock to be included. Normal trading volume has a value of 1 and 1.30 means that the volume at the specific day is 30% higher than the normal trading volume. The normal volume estimation is relative to the relevant region. AAR is average abnormal return, AV is average volume, AD-10:AD is 10 days prior the announcement day to the announcement day, AD:ED is announcement day to effective day, ED-1 is 1 day prior to the effective day, ED:ED+5 is effective day to 5 days after the effective day, ED:ED+15 is effective day to 15 days after the effective day.

		AD-10 : AD	AD : ED	ED-1	ED : ED+5	ED : ED+15
			Panel A: Additions			
U.S.	AAR	-0.02	0.07	0.24	-0.04	-0.01
	t-stat	-0.63	2.38	2.91	-1.06	-0.58
Global	AAR	0.02	0.13	0.76	-0.07	-0.01
	t-stat	0.73	5.16	6.09	-1.83	-0.56
Europe	AAR	0.02	0.10	0.63	0.05	0.00
	t-stat	0.54	2.92	3.95	0.80	-0.08
EM	AAR	0.02	0.15	0.76	-0.16	-0.07
	t-stat	0.50	3.73	4.30	-2.31	-2.20
U.S.	AV	1.12	1.16	1.47	1.13	1.12
	t-stat	2.61	4.71	7.62	3.32	3.69
Global	AV	1.03	1.21	1.74	1.15	1.10
	t-stat	1.26	5.79	9.91	5.22	4.66
Europe	AV	1.05	1.39	1.39	1.15	1.23
	t-stat	1.31	1.69	3.81	2.96	1.88
EM	AV	1.10	1.49	2.10	1.20	1.20
	t-stat	1.83	1.93	2.99	2.38	2.98

Table 2.8 - *continued*

Panel B: Deletions

U.S.	AAR	-0.06	-0.07	-0.14	-0.10	-0.02
	t-stat	-1.11	-1.45	-0.96	-0.86	-0.46
Global	AAR	-0.02	-0.11	-0.49	0.02	0.04
	t-stat	-0.46	-2.86	-3.71	0.35	1.30
Europe	AAR	0.03	-0.18	-0.94	-0.07	0.02
	t-stat	0.44	-2.30	-2.32	-0.88	0.34
EM	AAR	-0.06	-0.10	-0.91	0.22	0.08
	t-stat	-1.01	-1.78	-3.67	2.51	1.82
U.S.	AV	1.04	1.02	1.26	1.10	1.03
	t-stat	0.80	0.44	3.57	1.02	0.58
Global	AV	1.04	1.21	1.63	1.11	1.09
	t-stat	1.13	4.38	7.68	2.16	2.46
Europe	AV	0.95	1.06	1.24	1.01	0.96
	t-stat	-1.53	0.85	2.45	0.21	-0.96
EM	AV	0.93	1.00	1.41	0.93	0.89
	t-stat	-1.64	-0.07	2.49	-1.31	-3.20

Table 2.9: Change in analyst earnings forecast for new additions and deletions to the MSCI Minimum Volatility indices

Analyst earnings forecast change is calculated as the median analyst earnings forecast 10 days after the effective day minus the median analyst earnings forecast 10 days before the effective day (1 day before the announcement day). Current and following year median analyst earnings forecast is downloaded from IBES. Mean change in earnings forecast is measured in U.S. dollars per share, mean change in forecast standardized by price is measured as the change in eps forecast as percentage of price per share. Mean diff additions and deletions measures whether the number of additions and deletions is significantly different from the relevant number in the factor index. The sample consists of all new additions and deletion to one of the MSCI Minimum Volatility indices during the period November 2010 – December 2015 including a total of 11 rebalancing moments. MSCI USA Minimum Volatility (USD) index (U.S.), MSCI World Minimum Volatility (USD) index (Global), MSCI Europe Minimum Volatility (USD) index (Europe), and MSCI Emerging Markets Minimum Volatility (USD) index (EM).

		Δ eps forecast		Δ eps over P forecast	
		mean diff additions	mean diff deletions	mean diff additions	mean diff deletions
U.S.	mean	0.06	0.00	0.01%	0.00%
	t-stat	1.00	-0.04	0.59	-0.05
Global	mean	-0.15	-0.11	-0.02%	0.00%
	t-stat	-1.92	-1.14	-0.94	0.02
Europe	mean	-0.15	-0.26	0.02%	-0.20%
	t-stat	-0.94	-1.78	0.47	-1.79
EM	mean	0.09	0.07	-0.01%	-0.10%
	t-stat	1.44	1.31	-0.20	-2.07

Chapter 3

Does Earnings Growth Drive the Quality Premium?*

3.1. Introduction

Size, value and momentum factors have been dominating the empirical asset pricing literature over the past few decades.[3] However, recently two additional factors, namely profitability and investments, are considered of similar importance. Inspired by investment-based asset pricing, Hou et al. (2015) propose a four-factor model that adds an investment and a profitability factor to the market and size factors. Similarly, but motivated by the dividend discount model, Fama and French (2015) also add somewhat different versions of investment and profitability factors to their three-factor model (Fama and French, 1993). However, these two models still fail to explain the accruals effect documented by Sloan (1996)[4]. As the accounting-based variables mentioned above are also often seen as important determinants for investors' perception of firm quality (see, e.g., McGuire et al., 1990, Asness et al., 2014, or Trammell, 2014), they are also referred to as quality variables.[5]

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[*] This chapter is based on the paper of Kyosev, Hanauer, Huij, and Lansdorp (2018). The paper is under revise and resubmit in the *Journal of Banking and Finance*

[3] Cf. Basu (1977) for value, Banz (1981) for size, and Jegadeesh and Titman (1993) for momentum.

[4] See e.g. Fama and French (2016) and Hou et al. (2015) for the U.S. and Ammann et al. (2012) for countries from the European Monetary Union.

[5] Throughout the chapter, we use the terms "quality" and "accounting-based" interchangeably.

A notable observation regarding these accounting-based (quality) factors is the lack of a common element (despite that they are derived from accounting statements). While different definitions are also used to measure value (e.g., book-to-price and earnings-to-price), momentum (e.g., 6-minus-1-month return and 12-minus-1-month return), and low-risk (e.g., 36-month volatility and 52-week market beta), the dispersion in definitions is substantially larger for quality. Examples of anomaly variables that are seen as quality indicators are (derivations of) return-on-equity (Haugen and Baker, 1996), low accruals (Sloan, 1996), low investments (Cooper, Gulen, and Schill, 2008), low leverage (George and Hwang, 2010), or gross profitability (Novy-Marx, 2013). While there seems to be a consensus that quality measures have predictive power for the cross-section of future stock returns, there is no study which explains what drives the return differences and why some quality measures systematically work better than others.

Fama and French (2015) derive a theoretical relation between expected stock returns, profitability, and valuation based on a rewritten dividend-discount model as in equation (1).

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}}{B_t} \tag{3.1}$$

A crucial assumption of this model is that $Y_{t+\tau}$ stands for (expected) future profitability. In contrast, common accounting measures, amongst others also (past) company profitability, use lagged data. In this study, we investigate the relation between quality measures and both future profitability ($Y_{t+\tau}$ in the numerator of equation (1)) and expected returns (discount rate r in the denominator of equation (2)). To do so, we test the predictive power of quality measures for future one, three, and five year earnings growth. Furthermore, we document that only the variables that also predict future earnings also predict future stock returns while there is no relation for the variables without predictive power for future earnings. Finally, we test for a causal relationship by testing whether the predictive power of quality measures for the cross-section of future stock returns disappears once we control for future earnings growth.

Our main contribution is that we provide empirical evidence that the predictive power of quality variables for future returns originates from the variables being good proxies for future earnings growth. Although there seems to be a consensus in the literature that quality-related variables predict stock returns because they measure true economic profitability and have predictive power for future earnings (see, e.g., Sloan, 1996 and Novy-Marx, 2013), we are not aware of any empirical evidence supporting this notion in a direct way. Our paper builds on studies linking expected returns to implied cost of capital, such as Hou Van Dijk, and Zhang (2012). While Sloan (1996) and Novy-Marx (2013) show that quality measured by accruals or gross profitability, respectively, predict future earnings growth and stock returns, they do not provide evidence supporting a causal relation. In this study, we show that quality measures can predict future stock returns if and only if they are good proxies for future earnings growth. Quality variables which have no predictive power for future earnings growth also have no predictive power for the cross-section of future stock returns. Hence, the potential predictive power of quality measures for stock returns can be fully attributed to their predictive power for future earnings growth. As such this study is the first to provide empirical evidence supporting the conventional wisdom that quality is a measure of true economic profitability.[6]

Another contribution of our study is that we analyze the robustness of the predictive power of accounting-based factors in an international and multi-asset setting. Existing studies investigating quality factors have mainly been performed using U.S. equity data. We find robust results for the predictive power of quality measures for future stock returns in the U.S., Europe, Japan, global developed markets, and emerging markets. For additional robustness, we expand our analyses to the corporate bond markets and find consistent results – bonds issued by high-quality companies outperform those issued by low-quality companies if the quality measures used are good proxies for future earnings growth.

The remainder of the paper is organized as follows: Section 2 describes the data, quality definitions, and methodology. Section 3 presents our empirical results. Finally, Section 4 applies robustness tests, and Section 5 concludes.

[6] Our results are also consistent with the recent findings of Franke et al. (2017) that challenge a risk-based explanation for the profitability and investment factors.

3.2. Data, Quality definition, and methodology

In this section, we describe the data, quality variable definitions, and methodology used throughout this paper.

3.2.1. Data

Our sample comprises developed and emerging market stocks starting from December 1985 and December 1992, respectively, until December 2015. At the end of every month, we identify all constituents of the FTSE World Developed Index and the S&P/IFC Investable Emerging Markets Index for that particular month. We exclude financial firms as they are subject to special accounting standards and do not exhibit comparable values for some of our anomaly variables. The resulting developed global large-cap universe consists of approximately 1,600 stocks on average; the actual number ranges between about 1,200 and 1,900 over time. As many return anomalies are known to disappear or become significantly less pronounced when the universe is restricted to large-caps our choice of universe is rather conservative.[7] For emerging markets, we make a similar conservative choice by restricting our sample each month to the 500 biggest stocks as measured by market capitalization in USD.

We gather monthly stock returns taking into account dividends, stock splits and other capital adjustments. Our first data source for returns and outstanding shares is Interactive Data Exshare. In case this data is not available, we use MSCI return series instead. Alternatively, when neither of these is available, we calculate total returns using data from S&P/IFC. Monthly returns above 500% are truncated at this level. In addition to returns, we gather free-float adjusted market capitalization data from FTSE and S&P/IFC and fundamental data from Compustat and Worldscope. As a proxy for the risk-free rate, we obtain the 1-month U.S. Treasury bill rate from the data library of Kenneth French.

[7] Existing academic studies investigating the quality-type factors have mainly been performed using broad U.S. equity data that can be dominated by microcaps. E.g., Fama and French (2008) highlight that micro caps comprise on average only about 3% of the aggregated market cap of the NYSE-Amex-NASDAQ universe, but account for about 60% of the total number of stocks.

Our corporate bond dataset is based on the Barclays U.S. Corporate Investment Grade index and U.S. Corporate High Yield index during the period January 1994 – December 2015. Bond returns are provided by Barclays and accounting data is downloaded from Compustat and Worldscope. We only include bonds for companies with publicly traded equity due to the availability of accounting information. In the case of multiple bonds outstanding we include only one as we prefer 1) senior bonds over subordinated ones, 2) bonds in the maturity segment 5-15 years, 3) younger bonds, and 4) larger bonds. Our final sample consists of 403 investment grade bonds and 407 high yield bonds. We base our corporate bond analysis on returns in excess over duration matched treasuries as provided by Barclays. This allows us to focus on the default premium component of corporate bond returns and ignore the term premium which can be gained by investing in government bonds.

3.2.2. Quality definitions

In contrast to value, momentum, or low-risk factors, accounting-based factors show a considerable dispersion in definitions.[8] Therefore, this section provides an overview of the quality definitions applied, throughout the paper and motivates our variable choices.

Following the documentation of size, value, and momentum patterns in average stock returns, the Fama and French three-factor and Carhart four-factor models have been the "industry standard" in empirical asset pricing for many years. However, already Sloan (1996) shows that accruals are negatively related to future earnings and that higher accruals predict lower stock returns. Furthermore, researchers argued that companies with high return-on-equity (ROE, Haugen and Baker, 1996) and low investments proxied by total asset growth (Cooper et al., 2008) have high returns.

While Fama and French (2015) also use asset growth as a proxy for investments in their five-factor model, the findings of Novy-Marx (2013) could

[8] Value strategies have generally in common that they invest in stocks with a low price to their fundamentals, such as book value of equity, earnings, or dividends, while momentum strategies usually buy stocks that have had high returns over the past three to twelve months. Low-risk strategies typically invest in stocks with low beta or low volatility estimated over different time periods and frequencies.

explain why they do not use ROE as a proxy for future profitability. Novy-Marx (2013) finds that gross profitability as a top-line profitability measure is superior to bottom-line earnings in predicting future stock returns. The author argues that gross profitability performs better than ROE because it is the better proxy for true economic (expected) profitability.

Due to the long-standing discussion on an appropriate profitability definition, we also include variations of ROE, twelve months growth in return on equity (ROE growth) and earnings to sales (margins) to our list of quality variables.[9] Proxies for the safety of company such as debt to common equity (Leverage, George and Hwang, 2010) and volatility of earnings growth (Earnings variability, cf. Huang, 2009) complete our list. The detailed variable definitions can be found in the Appendix A.1. While we admit that there is still an ongoing discussion on whether these proxies can be further improved, the definitions used in this paper are the ones initially documented in the literature and therefore represent a conservative choice.[10]

3.2.3. Methodology

In this paper, we use two commonly accepted approaches, (i) cross-sectional Fama and MacBeth (1973) regressions to explain both future earnings growth and stock returns, and (ii) sorting stocks into portfolios based on quality variables.

To measure the predictive power of quality variables for future earnings growth, we follow the future earnings growth definition of Novy-Marx (2013) and use the cross-sectional regression approach of Fama and MacBeth (1973). More specifically, we run quarterly regressions on the one, three, and five-year change in earnings scaled by book equity on individual quality characteristics. First, we conduct univariate regressions to estimate the direct relation for each quality variable on future earnings growth. Furthermore, in multiple regressions, we include all quality variables and the standard control variables, beta, size (market cap), book-to-price, and momentum to estimate marginal

[9] Cf. also Piotroski (2000).

[10] See, for example, Thomas and Zhang (2002) and Richardson et al. (2005) for accruals, Pontiff and Woodgate (2008) for investments, or Ball et al. (2015, 2016) and Fama and French (2015) for profitability.

effects. This analysis determines which quality variables are really distinct and which have no marginal power to explain future earnings growth. All independent variables (firm characteristics) are winsorized at the 1st and the 99th percentiles and *t*-statistics are Newey-West adjusted using four lags.

We also conduct Fama and MacBeth (1973) regressions to answer which quality variables have power to predict returns. Next to the standard regression of next month returns on lagged characteristics we also predict three-year ahead returns as the dividend discount model in equation (1) makes a statement on rather long-term than short-term returns. Finally, we investigate whether a causal relationship between priced quality measures in the preceding regression and future earnings growth exists. Therefore, we also control for the *realized* future three-year growth in earnings (not known ex-ante). If some quality measures are only priced because they are a good proxy for future profitability one would expect that they become unpriced once controlled for future profitability. Again, all firm characteristics are winsorized at the top and bottom percentiles and *t*-statistics are Newey-West adjusted using three and 35 lags for regressions on monthly and three-year returns, respectively.

Finally, we construct equally-weighted quintile portfolios by ranking stocks on all the variables described above. For accruals, investments, earnings variability, and leverage measures, stocks with the lowest values are assigned to the top quintile, while for the remaining variables stocks with the highest factor scores are the top quintiles. We also form two composites of quality measures (‘Earnings non-predictive’ and ‘Earnings predictive) based on the outcome of the earnings prediction regressions in Table 3.1. The composites are constructed based on an equally-weighted combination of all individual variables' z-scores. For all variable sorts, factor scores are compared directly across all stocks, without imposing sector or country restrictions. However, we do control for regional effects in our global developed market sample by also presenting results for the U.S., Europe, and Japan in isolation. Portfolios are rebalanced monthly, and transaction costs are ignored throughout the analysis.

For the top, bottom, and top-minus-bottom (T-B) quintile portfolios, we report the annualized average returns (in USD and in excess of the risk-free rate), volatilities and Sharpe ratios. Furthermore, we also estimate the Fama and French – Carhart 4-factor alphas and coefficients for the T-B portfolios by running the following regression:

$$R_{T-B,t} = \alpha_{T-B} + \beta \cdot \left(R_{M,t} - R_{f,t}\right) + s \cdot SMB_t + h \cdot HML_t + w \cdot WML_t + \varepsilon_{T-B,t} \quad (3.2)$$

where $R_{T-B,t}$ is the difference of the top and bottom portfolio returns in period t, $R_{f,t}$ is the risk-free return in period t, α_{T-B} is the alpha of top minus bottom portfolio, $R_{M,t}$ is the return on t market portfolio in period t, and β, s, h, and w are the estimated factor coefficients. Global and regional size (small-minus-big, SMB), value (high-minus-low, HML) and momentum (winner-minus-loser, WML) factors are calculated by ranking stocks, on their market capitalization, book-to-market ratio and past 12-minus-1 month local total return respectively, and taking the difference in return between the equally-weighted top and bottom terciles.

A consistent rank portfolio approach is used for our corporate bond analysis – we form equally-weighted quintile portfolios. Due to the systematically lower liquidity of corporate bonds compared to equities, we substitute the one month holding period, used for equities, with twelve months holding period. To do so, we use the overlapping portfolio approach of Jegadeesh and Titman (1993). We split the corporate bond universe into investment grade and high yield as they are effectively seen as two different asset classes by practitioners and academics (e.g., Ambastha et al., 2010).

3.3. Empirical Results

In this section, we conduct a set of empirical tests to shed more light on the common quality indicators. First, we test which of the widely used quality measures are forward-looking indicators for firm profitability. That is which ones have predictive power for future earnings growth. Second, we compare the performance of hypothetical global investment strategies based on the same set of quality definitions. Third, we create two competing quality strategies – earnings predictive and earnings non-predictive – and compare their performance across multiple settings. Finally, we perform a regional analysis to verify that the global effect is not a result of systematic regional allocation bets. For further robustness, we extend our analysis to emerging markets and corporate bonds.

3.3.1. Quality and growth in future profitability

A common feature of all quality characteristics is that they use accounting information measuring backward looking firm productivity. In the spirit of the dividend-discount model as in Fama and French (2015) , however, expected future profitability is crucial and good quality variables should capture the true productivity of a company. A common indicator that financial analysts, as well as media, look at is surprise in earnings. This overlaps with the definition of Sloan (1996) and Novy-Marx (2013) that quality is a measure of true economic profitability and that it has strong predictive power for future earnings.
In Table 3.1 we show results of Fama-Macbeth (1973) regressions of one, three, and five-year growth in earnings on individual quality characteristics and we focus on the three-year change result within the text. The results for the other two periods are, however, similar.

The column '3Y change univariate' shows average univariate regression coefficients. Consistent with the studies of Sloan (1996) and Novy-Marx (2013), high gross profitability, low accruals, and low investments positively predict future earnings growth with coefficients 2.48 (t-stat 2.06), -34.59 (t-stat -8.25), and -16.00 (t-stat -5.54) respectively. On the other hand, high ROE, high margins, high ROE growth, low leverage, and low earnings variability are associated with a negative change in future earnings. This indicates that profitability measures based on earnings tend to mean revert and investors who want to capture future profitability should discount past earnings information when making inferences for true firm profitability.

In a univariate Fama Macbeth setting earnings-based measures and leverage all have significant predictive power for one, three, and five years earnings growth but with the opposite to the expected sign. This means that quality strategies based on these measures will suffer from negative profitability changes. Looking back at the dividend discount model predictions in equation (1), negative expected earnings means that higher expected returns do not immediately stem from the theoretical model. On the other hand, high gross profitability, low accruals, and low investments, all scaled by assets, positively predict earnings growth at all horizons meaning that

Table 3.1: Predictive power of quality measures for one, three, and five years future earnings growth

The table reports results of Fama-MacBeth (1973) regressions of future one, three, and five-year growth in earnings scaled by book equity $\left(\frac{Earnings_{t+r} - Earnings_t}{BE_t}\right)$ on individual firm characteristics. Characteristics are calculated according to Appendix A and winsorized at 1% level. t-statistics are Newey-West adjusted using four lags and are shown in brackets. Regressions are run on quarterly data during the period January 1986 - December 2015 for our Global markets sample. The column 'univariate' shows the average univariate regression coefficient for the respective quality measure. The column 'multiple' shows marginal predictive power of the quality measures, controlling for other quality, and firm characteristics. In brackets (+) or (-) is the expected sign of the coefficient.

	1Y change		3Y change		5Y change	
	univariate	multiple	univariate	multiple	univariate	multiple
ROE (+)	-25.44	-33.88	-38.77	-49.02	-36.39	-52.89
	[-10.44]	[-12.55]	[-9.05]	[-12.51]	[-8.20]	[-13.09]
Margins (+)	-9.68	-2.94	-14.12	-2.54	-11.83	0.32
	[-10.75]	[-5.28]	[-10.35]	[-1.74]	[-6.86]	[0.20]
ROE growth (+)	-26.16	-13.15	-37.46	-13.94	-46.98	-22.90
	[-11.64]	[-9.82]	[-10.54]	[-6.73]	[-13.89]	[-8.09]
Leverage (-)	1.17	0.10	2.51	0.80	3.05	1.66
	[5.28]	[0.52]	[6.34]	[2.55]	[6.45]	[5.00]
Earnings (-) variability	0.28	0.04	0.46	0.03	0.40	0.00
	[5.41]	[2.31]	[5.12]	[0.79]	[3.92]	[0.04]
Gross profitability (+)	1.38	0.43	2.48	4.35	5.52	6.43
	[2.18]	[0.73]	[2.06]	[3.51]	[3.94]	[3.39]
Accruals (-)	-19.81	-3.23	-34.59	-10.05	-38.88	-13.76
	[-6.84]	[-2.77]	[-8.25]	[-5.58]	[-7.81]	[-4.74]
Investments (-)	-10.18	-3.87	-16.00	-7.52	-13.48	-6.42
	[-4.53]	[-3.72]	[-5.54]	[-4.75]	[-4.10]	[-2.93]
ln(mcap)		-0.03		-0.15		-0.26
		[-0.36]		[-1.65]		[-1.36]
ln(Book-to-price)		-7.03		-9.18		-10.63
		[-13.80]		[-16.39]		[-10.93]
Momentum 12-1		8.24		7.92		5.48
		[13.86]		[6.67]		[4.04]
Beta 3Y		-0.63		-1.25		-1.38
		[-1.48]		[-2.29]		[-3.30]

all else equal, they should have higher expected returns. In a multiple regression framework, we test the marginal predictive power of our set of quality measures after controlling for other firm characteristics and results remain qualitatively similar. Gross profitability, Accruals, and Investments correctly predict earnings growth across all horizons. It is also important that they remain significant when included simultaneously in the regression meaning that they contain different information about future profitability. ROE, Margins, ROE growth, Leverage, and earnings variability either predict earnings growth with an opposite to the expected sign or have no predictive power.

3.3.2. Quality and stock returns

In this section, we look at the discount rate side of the dividend discount model. We test whether quality measures which can predict earnings growth also predict returns, as predicted by equation 1.

Table 3.2 shows cross-sectional regression results of short-term and long-term returns on our set of quality indicators, controlling for firm size, valuation, past returns, and market beta. Panel A contains a standard Fama Macbeth analysis of next month returns on lagged characteristics. If the dividend discount model predictions hold only the earnings predictive characteristics should have significant coefficients. Our results confirm this theoretical prediction as gross profitability, accruals, and investments are the only three measures which have predictive power for stock returns with coefficients of 0.98 (*t*-stat 4.66), -1.01 (*t*-stat -2.67), and -0.64 (*t*-stat -2.75) respectively. The remaining characteristics, except for earnings variability and leverage, have coefficients which correspond to the expected sign but are not statistically distinguishable from zero. As the dividend discount model refers rather to long-term expected returns than short-term returns we also investigate the predictive power of quality indicators for longer term returns. In Panel B we show Fama Macbeth regressions of three-year stock returns on the same set of quality characteristics and control variables. The coefficient on gross profitability, accruals, and investments remain significant, while the remaining quality variables are still insignificant which confirms that only earnings predictive measures have predictive power for future stock returns.

Table 3.2: Predictive power of quality measures for stock returns

Table 3.2 reports the results of Fama-MacBeth (1973) regressions of stock returns on individual firm characteristics. Characteristics are calculated according to Appendix A and winsorized at 1% level, t-statistics are Newey-West adjusted using three lags for 1 month return regressions and 35 lags for 36-month return regressions. All regressions correct for the following set of control variables (Controls): log(Mcap), log(Book-to-price), Beta 3Y, and Momentum 12-1M. The last row shows the average adjusted R-squared. Results are calculated on monthly data for the period January 1986 - December 2015 for our Global markets sample. Panel A shows standard Fama-MacBeth univariate regression with next month returns. Panel B shows results of univariate regressions of future three-year returns on the respective quality measure. Panel C controls for change in future three years earnings change $\left(\frac{Earnings_{t+r} - Earnings_t}{BE_t}\right)$. Every column represents regressions for the respective quality measure, in brackets (+) or (-) is the expected sign of the coefficient.

	ROE (+)	Margins (+)	ROE growth (+)	Leverage (-)	Earnings variability (-)	Gross profits (+)	Accruals (-)	Investments (-)
Panel A: Regressions of next month returns on quality measures								
Intercept	1.22	1.28	1.22	1.24	1.24	1.02	1.12	1.23
	[2.98]	[3.10]	[2.99]	[3.09]	[3.06]	[2.45]	[2.73]	[3.00]
Quality measure	0.53	0.14	0.09	0.00	0.00	0.98	-1.01	-0.64
	[1.78]	[0.79]	[0.49]	[0.03]	[0.42]	[4.66]	[-2.67]	[-2.75]
Controls	yes	yes	yes	yes	yes	yes	yes	yes
R-sq	7.91	8.01	7.64	7.77	7.64	7.93	7.29	7.81
Panel B: Regressions of next three year returns on quality measures								
Intercept	38.30	39.13	37.94	38.74	37.42	33.72	34.81	38.77
	[2.20]	[2.29]	[2.22]	[2.31]	[2.21]	[1.86]	[2.02]	[2.23]
Quality measure	16.42	13.25	-2.84	0.84	0.02	22.26	-33.01	-20.70
	[1.38]	[1.91]	[-0.53]	[0.59]	[0.17]	[2.24]	[-2.42]	[-2.31]
Controls	yes	yes	yes	yes	yes	yes	yes	yes
R-sq	8.98	9.08	8.48	8.64	8.38	9.30	7.72	8.75
Panel C: Regressions of next three year returns on quality measures, controlling for change in future earnings								
Intercept	31.16	36.17	35.16	35.80	34.38	28.73	31.88	34.94
	[1.96]	[2.24]	[2.18]	[2.26]	[2.13]	[1.67]	[1.94]	[2.12]
Quality measure	90.62	32.86	43.76	-1.13	-0.28	26.08	-4.64	-0.20
	[5.28]	[4.39]	[9.64]	[-0.82]	[-3.39]	[2.98]	[-0.38]	[-0.02]
Δ Earnings	132.3	116.08	117.72	108.29	109.40	106.81	108.61	107.28
	[10.4]	[11.2]	[11.3]	[10.2]	[10.6]	[10.3]	[10.4]	[10.4]
Controls	yes	yes	yes	yes	yes	yes	yes	yes
R-sq	0.24	0.22	0.2	0.20	0.20	0.21	0.20	0.20

Since the dividend discount model states that, all else equal (e.g. book-to-market), higher future earnings imply higher expected stock returns, the effects described above should be explained after controlling for the relevant information. Therefore, in Panel C we augment our regression specification and regress three year returns on quality characteristics, controlling for three year growth in earnings and the same control variables as in Panel B. This adjustment makes the results exactly the opposite to the ones in Panels A and B. Accruals and Investments become insignificant while only gross profitability keeps its significance with a t-statistic of 2.98. On the other hand, all other characteristics with the exception of Leverage – ROE, Margins, past ROE growth, and Earnings variability – become significant after controlling for the negative earnings growth associated with them. Finally, the coefficient on change in earnings is highly significant in all regressions with t-statistics around 10. These results have important implications for the causality of the relationship between quality indicators and stock returns. They show that what is driving returns is future earnings growth and different measures used to define quality are effectively different ways to predict earnings growth. It also shows that earnings are highly relevant information as all earnings based characteristics are significantly related to stock returns after controlling for earnings mean reversion associated with them. All in all, our results indicate that a true quality definition should include measures that positively predict earnings growth and the abnormal returns will follow as a result of that.

3.3.3. Performance of quality strategies

In this section we split quality measures in two groups - earnings non-predictive (ROE, Margins, ROE growth, Leverage, Earnings variability) and earnings predictive (Gross profitability, Accruals, Investments) and investigate the performance of hypothetical trading strategies based on them. In the first part of the analysis, we present the performance of top, bottom, and the top-minus-bottom (henceforth T-B) quintile portfolios.

Panel A of Table 3.3 shows the performance of strategies based on the quality characteristics which are not associated with positive earnings growth. We also create an overall quality measure ‘Combined’ by constructing a strategy which uses an equally-weighted combination of all individual variables.

Focusing on the T-B quintile portfolios we see that all of them produce positive returns and ROE seems to be superior to the rest with a return of 3.1%. Due to short sale constraints practitioners often focus on the top quintile portfolio. Therefore, we also present separate results for the long and the short leg of the self-financing portfolio. By looking at the top quintile portfolio we notice that,

Table 3.3: Performance of earnings non-predictive quality measures

In Table 3.3 we show performance characteristics for multiple quality strategies. Panel A consists of returns, volatilities, and Sharpe ratios for Top, Bottom, and Top minus Bottom (T-B) portfolios sorted on the relevant factor. Top is the portfolio with the highest 20% ranked stocks, Bottom is the portfolio with the lowest 20% ranked stocks, and T-B is a self-financing portfolio which is long the top 20% stocks (Top) and short the bottom 20% stocks (Bottom). The factors are calculated as explained in Appendix A. Returns and volatilities are estimated based on monthly data and then annualized. Panel B contains regression coefficients based on Fama and French / Carhart 4-factor model. The factors used are based on our replication of original factors and are based on the investment universe used for the analysis. Alphas are annualized. The sample period is January 1986 - December 2015.

		ROE	Margins	ROE growth	Leverage	Earnings variability	Combined	Universe
Panel A: Performance of Top, Bottom, and Top-minus-Bottom portfolios								
	Return	9.7%	8.3%	8.2%	7.8%	9.1%	9.5%	8.2%
Top	Volatility	15.8%	15.3%	17.0%	16.0%	13.3%	14.9%	16.0%
	Sharpe ratio	0.61	0.54	0.48	0.49	0.69	0.64	0.52
	Return	6.6%	7.4%	7.9%	7.6%	8.0%	7.5%	
Bottom	Volatility	20.0%	20.6%	18.8%	16.1%	18.3%	19.7%	
	Sharpe ratio	0.33	0.36	0.42	0.47	0.44	0.38	
	Return	3.0%	0.9%	0.4%	0.2%	1.0%	2.0%	
T-B		[1.41]	[0.35]	[0.27]	[0.15]	[0.69]	[0.99]	
	Volatility	11.5%	13.3%	6.8%	7.6%	8.1%	10.9%	
	Sharpe ratio	0.26	0.07	0.05	0.03	0.13	0.19	
Panel B: Fama and French 4-factor regression coefficients								
	alpha	2.6%	2.0%	0.0%	0.5%	4.1%	3.1%	
		[1.49]	[1.03]	[-0.03]	[0.38]	[3.68]	[2.04]	
	Mkt-RF	-0.06	-0.14	-0.05	-0.05	-0.27	-0.17	
		[-1.86]	[-3.71]	[-2.09]	[-1.70]	[-12.14]	[-5.47]	
	SMB	-0.43	-0.82	0.11	0.26	-0.19	-0.45	
		[-4.80]	[-8.31]	[1.84]	[3.64]	[-3.31]	[-5.65]	
	HML	0.16	0.47	-0.16	-0.35	-0.03	0.16	
		[2.19]	[5.79]	[-3.20]	[-6.07]	[-0.62]	[2.43]	
	WML	0.31	0.21	0.19	0.08	0.07	0.25	
		[7.87]	[4.70]	[7.15]	[2.52]	[2.70]	[6.94]	
	R-sq	0.38	0.43	0.19	0.10	0.47	0.46	

with the exception of Leverage and ROE growth, all variables outperform the market portfolio. The combined quality strategy generates a T-B quintile return of 2.0%.

Controlling for the standard risk factors such as market beta, size, value, and momentum, Panel B shows a similar picture. The strongest variable (ROE) has positive loadings on the value and momentum factors and the alpha of 2.6% per annum is again not statistically different from zero (*t*-statistic of 1.49). In terms of factor loadings, the combined quality strategy is similar to ROE in terms of factor loadings but results in a marginally significant alpha of 3.1% per annum (*t*-stat 2.04). One variable that stands out is Earnings variability with a four-factor alpha of 4.1% per annum (*t*-statistic of 3.68). Its market loading of -0.27 (*t*-statistic of -12.14) hints that it behaves like another well-known effect, namely the low-risk effect documented by Black, Jensen, and Scholes (1972), Blitz and van Vliet (2007), and Frazzini and Pedersen (2014). Results from Panel A confirm this notion as the top portfolio has a volatility of 13.3% and the bottom – 18.4% compared to market volatility of 16.0%. Therefore, its usage as a quality indicator is questionable since it can also be seen as a low-risk measure.

In Table 3.4 we show similar information but now for quality characteristics that are associated with positive future earnings growth. Panel A shows that the T-B portfolios for all three characteristics have positive returns: 4.0% for Gross profitability, 2.6% for Accruals and 3.2% for Investments. Furthermore, all top quintile portfolios also outperform the total market portfolio. The combined quality definition clearly benefits from diversification as it has better performance than each individual characteristic (T-B return of 5.1% with comparable volatility). The earnings predictive definitions remain strong after correcting for other risk factors as each individual factor has a highly significant alpha. Novy-Marx (2013) has documented that stocks with high gross profitability tend to be relatively more expensive and that a good working investment approach is to combine profitability and value or the so-called 'quality at a reasonable price' strategy. Our global results point in the same direction as Gross profitability has a negative (but insignificant) loading on HML. However, Table 3.2 indicates that an investor can also achieve a performance improvement by diversifying across

Table 3.4: Performance of earnings predictive quality measures

In Table 3.4 we show performance characteristics for multiple quality strategies. Panel A consists of returns, volatilities, and Sharpe ratios for Top, Bottom, and Top minus Bottom (T-B) portfolios sorted on the relevant factor. Top is the portfolio with the highest 20% ranked stocks, Bottom is the portfolio with the lowest 20% ranked stocks, and T-B is a self-financing portfolio which is long the top 20% stocks (Top) and short the bottom 20% stocks (Bottom). The factors are calculated as explained in Appendix A. Returns and volatilities are estimated based on monthly data and then annualized. Panel B contains regression coefficients based on Fama and French / Carhart 4-factor model. The factors used are based on our replication of original factors and are based on the investment universe used for the analysis. Alphas are annualized. The sample period is January 1986 - December 2015. Returns of the top and bottom portfolios are in excess of the risk-free rate.

		Gross profitability	Accruals	Investments	Combined	Universe
Panel A: Performance of Top, Bottom, and Top-minus-Bottom portfolios						
Top	Return	10.1%	9.2%	9.6%	10.4%	8.2%
	Volatility	14.7%	17.1%	17.1%	15.8%	16.0%
	Sharpe ratio	0.68	0.54	0.56	0.66	51.5%
Bottom	Return	6.1%	6.6%	6.4%	5.2%	
	Volatility	16.9%	17.3%	18.7%	18.4%	
	Sharpe ratio	0.36	0.38	0.34	0.29	
T-B	Return	4.0%	2.6%	3.2%	5.1%	
		[2.79]	[2.44]	[1.93]	[3.75]	
	Volatility	7.7%	5.6%	8.9%	7.3%	
	Sharpe ratio	0.52	0.46	0.36	0.71	
Panel B: Fama and French 4 factor regression coefficients						
	alpha	5.3%	2.8%	3.2%	6.0%	
		[4.10]	[2.66]	[2.38]	[5.04]	
	Mkt-RF	-0.11	0.01	-0.08	-0.11	
		[-4.35]	[0.35]	[-2.81]	[-4.65]	
	SMB	-0.18	-0.24	0.01	-0.25	
		[-2.73]	[-4.40]	[0.19]	[-3.99]	
	HML	-0.07	0.14	0.52	0.38	
		[-1.32]	[3.07]	[8.97]	[7.54]	
	WML	0.08	-0.02	-0.05	0.00	
		[2.62]	[-0.90]	[-1.75]	[-0.03]	
	R-sq	0.22	0.05	0.36	0.25	

multiple quality signals. The combined earnings predictive quality strategy has an alpha of 6.0% per annum (*t*-statistic of 5.04) which is substantially higher than gross profits, accruals, and investments stand alone. Further, the earnings predictive quality factor is superior to the earnings non-predictive one for both T-B raw returns and after correcting for risk factors.

3.4. Robustness tests

3.4.1. Regional and emerging markets results

In this section, we extend the scope of the study as well as check for robustness of our results across regions. Section 3 presents results on global large capitalization stocks which are commonly used as an investment universe by practitioners. Our findings confirm previously documented U.S. results on profitability, accruals, and investments. However, what we find could potentially be driven by a strong systematic U.S. bias in the data which results in us effectively comparing the performance of the U.S. to non-U.S. stocks. As such, we aim to provide evidence that the global results are not just the result of some systematic regional allocation bets. We therefore further split the Global universe into three main regions – United States, Europe, and Japan as well as add Emerging markets for additional out of sample robustness tests.

Table 3.5 summarizes the performance for the two combined quality strategies – Earnings non-predictive and Earnings predictive. The main takeaway is that the combined 'earnings predictive' strategy consistently outperforms 'earnings non-predictive' one based on both T-B returns as well as alphas. Panel A compares the long-short return of the two strategies. Focusing on the combined 'earnings predictive' definition we see that the T-B returns for the United States are highest within global developed markets. Furthermore, the composite 'earnings predictive' quality factor yields positive returns in all regions (significant with the exception of Japan). On the other hand, the 'earnings non-predictive' quality definition does not exhibit returns which are statistically distinguishable from zero. Finally, the emerging market results reinforce the superiority of the 'earnings predictive' definition over the 'earnings non-predictive' one. These results can serve as a true out-of-sample test as this universe is much less looked at in academic studies. Correcting for other risk

Table 3.5: International performance of earnings predictive and earnings non-predictive quality factors

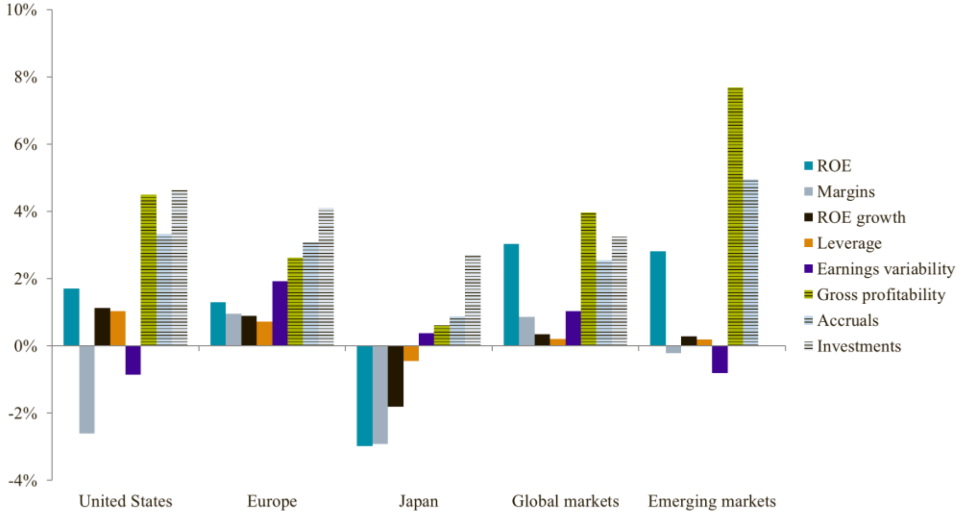
In Table 3.5 we show returns and alphas of the combined earnings non-predictive and earnings predictive quality definitions for multiple regions. Panel A shows returns of Top minus Bottom (T-B) quality portfolios. T-B is a self-financing portfolio which is long the top 20% stocks (Top) and short the bottom 20% stocks (Bottom). Returns are estimated based on monthly data and then annualized. Panel B contains annualized 4-factor Fama and French / Carhart alphas per region. The factors used are based on our replication of original factors using the same investment universe as used for the analysis. The universe definitions of the United States, Europe, and Japan are based on carveouts of these regions from our Global markets universe. Emerging markets universe is based on the biggest 500 stocks measured by market capitalization. The sample period is January 1986 - December 2015 for Global markets, the United States, Europe, and Japan and January 1993 - December 2015 for Emerging markets.

	Earnings non-predictive	Earnings predictive
Panel A: Top-minus-Bottom return differential		
United States	1.1%	6.5%
	[0.47]	[3.79]
Europe	2.8%	5.2%
	[1.45]	[4.05]
Japan	-2.9%	2.8%
	[-1.06]	[1.75]
Global markets	2.0%	5.1%
	[1.02]	[3.86]
Emerging markets	0.9%	6.2%
	[0.37]	[2.66]
Panel B: Fama and French 4 factor alphas		
United States	3.3%	6.7%
	[2.15]	[4.06]
Europe	4.7%	5.2%
	[3.20]	[4.01]
Japan	2.6%	2.7%
	[1.11]	[1.66]
Global markets	3.1%	6.0%
	[2.04]	[5.04]
Emerging markets	5.6%	8.7%
	[2.87]	[4.09]

factors in Panel B yields similar conclusions meaning that the results cannot be attributed to the well-known factors such as size, value, and momentum.

Figure 3.1: International performance of different quality characteristics

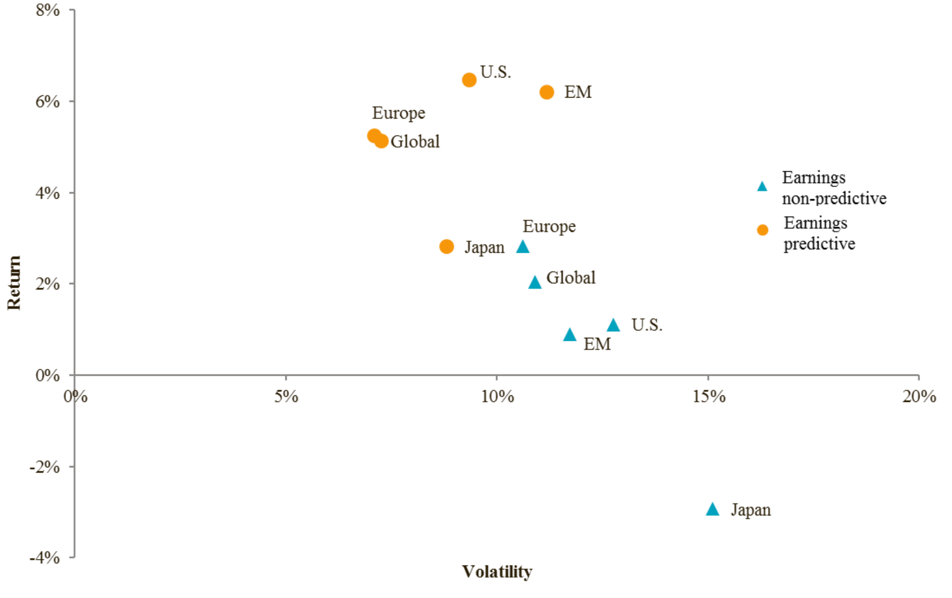
In Figure 3.1 we show Top-minus-Bottom (T-B) returns of the alternative quality definitions for multiple regions. T-B is a self-financing portfolio which is long the top 20% stocks (Top) and short the bottom 20% stocks (Bottom). Returns are estimated based on monthly data and then annualized. The universe definitions of the United States, Europe, and Japan are based on carve-outs of these regions from our Global markets universe. Emerging markets universe is based on the biggest 500 stocks measured by market capitalization. The sample period is January 1986 - December 2015 for Global markets, the United States, Europe, and Japan and January 1993 - December 2015 for Emerging markets.



The results for individual variable reinforce our conclusions. Figure 3.1 shows that within every region earnings predictive measures (Gross profitability, Accruals, and Investments) and stronger than the earnings non-predictive ones. Furthermore, all ‘earnings predictive’ variables have positive T-B quintile returns in all regions (though returns for gross profitability is weak in Japan and Investments – in Emerging markets). On the other hand, for the ‘earnings non-predictive’ definitions we find mixed results across regions.

Figure 3.2: International performance of different quality characteristics

In Figure 3.2 we show volatility-return scatter plots of the Earnings non-predictive and Earnings predictive Quality definitions per region. Results apply for a Top-minus-Bottom (T-B) self-financing portfolio which is long the top 20% stocks (Top) and short the bottom 20% stocks (Bottom). Returns and volatilities are estimated based on monthly data and then annualized. The universe definitions of the United States, Europe, and Japan are based on carve-outs of these regions from our Global markets universe. Emerging markets (EM) universe is based on the biggest 500 stocks measured by market capitalization. The sample period is January 1986 - December 2015 for Global markets, the United States, Europe, and Japan and January 1993 - December 2015 for Emerging markets.



A further examination of the two strategies is shown in Figure 3.2 which plots their regional performance in the volatility-return space. There we see consistently high Sharpe ratios for 'earnings predictive' quality definitions across regions compared to its 'earnings non-predictive' counterpart.

3.4.2. Cross-sectional regressions

After documenting the standalone portfolio returns and four-factor model alphas in the previous two sections, we are now interested in which quality variables carry unique information and whether this holds in an international setup. Therefore, we employ the Fama and MacBeth (1973) methodology to estimate the marginal effects of the single quality variables after controlling for each other.

In Table 3.6 we estimate the marginal effects of the single quality variables after controlling for each other, all controlled for the standard factors size, beta, value, and momentum. Starting with our Global sample we see that the marginal predictive power of the earnings predictive variables – Gross profitability, Accruals, and Investments – have significant predictive power for future stocks returns while with the exception of ROE, the non-earnings predictive variables also have no marginal predictive power for stock returns. When we split the sample into sub-regions – United States, Europe, and Japan - results remain qualitatively similar and earnings predictive measures have systematically stronger predictive power compared to earnings non-predictive ones. A region that stands out is Japan where quality, in general, has weak performance and, except for Leverage, the coefficients are insignificant, albeit with the expected signs. In Emerging Markets the same relationship generally hold with the exception that ROE has positive marginal predictive power for stock returns and Investments negative but insignificant.

Table 3.6: Regional Fama-MacBeth (1973) regressions

Table 6 reports results of Fama-MacBeth (1973) regressions of monthly stock returns on individual firm characteristics. Characteristics are calculated according to Appendix A and winsorized at 1% level, t-statistics are Newey-West adjusted using three lags. The last row shows the average adjusted R-squared. The sample period is January 1986 - December 2015 for Global markets, United States, Europe, and Japan and January 1993 - December 2015 for Emerging markets. The universe definitions of United States, Europe, and Japan are based on carveouts of these regions from our Global markets universe. Emerging markets (EM) universe is based on the biggest 500 stocks measured by market capitalization. In brackets (+) or (-) is the expected sign of the coefficient.

	United States		Europe		Japan		Global		EM	
	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
Intercept	1.36	3.07	1.02	2.14	1.32	1.87	0.86	2.19	0.85	1.33
ROE (+)	0.59	1.63	0.47	1.44	0.36	0.38	0.69	2.04	1.93	2.82
Margins (+)	-0.02	-0.13	0.27	0.51	1.07	0.66	0.16	0.89	-0.34	-1.09
ROE growth (+)	-0.50	-2.06	-0.07	-0.25	-0.12	-0.17	-0.22	-0.79	-0.92	-1.48
Leverage (-)	0.00	-0.08	-0.06	-1.29	0.15	2.64	0.04	1.12	-0.03	-0.22
Earnings Variability (-)	0.00	-0.91	-0.01	-1.09	-0.01	-0.96	0.00	-0.21	-0.01	-0.85
Gross profitability (+)	0.66	2.57	0.68	3.22	0.60	1.52	0.91	4.37	1.87	2.92
Accruals (-)	-1.29	-2.43	-0.46	-1.01	-0.89	-1.44	-1.03	-2.75	-1.51	-2.18
Investments (-)	-0.33	-1.23	-0.50	-2.23	-0.37	-0.87	-0.51	-2.59	-0.08	-0.18
ln(mcap)	-0.07	-1.76	-0.03	-0.88	-0.06	-0.98	-0.02	-0.67	-0.07	-1.10
Beta 3Y	-0.03	-0.17	-0.01	-0.04	0.06	0.37	-0.09	-0.59	0.16	0.60
ln(Book-to-price)	0.20	2.15	0.29	3.48	0.85	5.94	0.35	4.21	0.60	3.88
Momentum12-1	0.38	1.31	1.27	4.00	0.33	0.94	0.85	3.21	0.86	3.44
R-sq	10.97		9.46		15.42		9.42		9.65	

3.4.3. Corporate bonds

With this section, we aim at two main objectives. First, gather strong evidence for the robustness of quality as a factor by testing it in a fundamentally different setting than previously done in the literature. Second, stimulate future research on the existence of similar underlying return drivers across asset classes (e.g. Bhojraj and Swaminathan, 2009, Correia et al, 2012, Jostova et al., 2013, Haesen et al., 2017, or Houweling and Van Zundert, 2017).

To do so we directly apply our 'earnings non-predictive' and 'earnings predictive' combined quality definitions from the previous section. Corporate bonds fundamentally differ from equities with features such as maturity date, duration, and interest rate risk. The latter one has no impact on our results due to using excess returns over duration matched securities, focusing on the default premium. Nevertheless, we acknowledge that for a proper quality definition further adjustments to the variables could be made. Using simple equity quality definitions makes our results conservative.

Table 3.7 shows performance statistics for both investment grade and high yield bonds. The top portfolio investment grade bonds based on both quality definitions outperforms the market in terms of excess return as well as on a risk-adjusted basis (Sharpe ratios of 0.15 and 0.22 compared to 0.08 for the market) showing evidence for a quality premium. The 'earnings predictive' definition stands out in terms of identifying 'low quality' bonds as the bottom portfolio performs worse than the bottom industry portfolio and the market portfolio. These results in a significant top-minus-bottom premium 0.6% (*t*-stat 1.99) for the 'earnings predictive' definition compared to 0.0% for the 'earnings non-predictive' one.

Table 3.7: Corporate bonds analysis

In Table 7 we show performance characteristics for the Earnings predictive and Earnings non-predictive quality strategies for U.S. Investment Grade and U.S. High Yield corporate bonds. To calculate the return in month *t* we take the average return of the portfolios constructed from month *t-11* to *t*. Each month the universe is split in 5 portfolios sorted on the relevant factor as Top means the 20% highest quality bonds, and Bottom – 20% lowest quality bonds. T-B is the difference between the return of the Top portfolio and the return of the Bottom portfolio. Investment grade is defined as stocks with credit ratings AAA, AA, A, BBB; High Yield – BB, B, CCC, CC, C. Returns and volatilities are calculated based on monthly data and then annualized. The sample period is January 1994 - December 2015.

		Investment Grade			High Yield		
		Earnings non-predictive	Earnings predictive	Market	Earnings non-predictive	Earnings predictive	Market
Top	Return	0.5%	0.8%	0.3%	2.7%	4.7%	1.7%
	Volatility	3.60%	3.78%	4.27%	8.59%	10.10%	9.42%
	Sharpe ratio	0.15	0.22	0.08	0.32	0.47	0.18
Bottom	Return	0.5%	0.2%		1.4%	0.4%	
	Volatility	4.71%	4.62%		13.09%	11.97%	
	Sharpe ratio	0.11	0.04		0.11	0.03	
T-B	Return	0.0%	0.6%		1.3%	4.3%	
		[0.00]	[1.99]		[0.86]	[3.57]	
	Volatility	1.64%	1.50%		6.94%	5.70%	
	Sharpe ratio	0.00	0.42		0.18	0.76	

The results for high yield bonds show strong evidence that an investment strategy based on quality can also be profitable, if applied in corporate bond markets. Furthermore, the superiority of the 'earnings predictive' definition proves robust once again with a top-minus-bottom premium of 4.3% (*t*-stat of 3.57) compared to 1.3% for the 'earnings non-predictive' definition. The better performance of quality among high yield bonds relative to the performance in investment grade bonds can be partially attributed to the relative riskiness of both segments. In corporate bonds, the downside risk, heavily influenced by defaults, is generally much higher than the upside potential. A closer examination of the risk and return profiles of the top and bottom quality portfolios hints that investing in high-quality bonds effectively lowers the risk of default, as well as earns a return premium.

3.4.4. Quality and other factor premiums

Finally, we discuss the relation between quality-related and other factor premiums to address the question of whether it is a separate factor or just a reframing of already documented effects. The results of the previous sections show that the earnings predictive quality definition seems to be a robust and also sizeable new factor as the premiums exist within several regions and based on a large-cap investable sample. For the 'earnings non-predictive' quality definition, however, we observed overall weaker results. Furthermore, some observations such as the low beta of the Earnings variability variable raise the question if there is some overlap between factors. Naturally, the answer to this question depends on the exact definition of the anomaly which we aim to clarify with this paper. Apart from the single factor academic definitions of among others Sloan (1996), Novy-Marx (2013), and Fama and French (2015), the studies of Piotroski (2000) and Asness et al. (2014) propose more complex quality factor composition consisting of multiple characteristics separated in thematic groups. One of these groups – namely stability - is also related to the low-risk anomaly documented by Black, Jensen, and Scholes (1972), and Blitz and van Vliet (2007).

To give some new insights to this discussion we aim to elaborate on how the 'earnings non-predictive' and 'earnings predictive' definitions overlap with other factors. However, unlike in section 3.1, we do not focus on returns but rather on the underlying stocks that are favored by the two approaches.

Figure 3.3: Rank correlation between quality and other factors

In Figure 3.3 we show the average rank correlation of the Earnings predictive and Earnings non-predictive Quality definitions with Book to Price, the negative of Market capitalization in USD (Market cap), past 12 minus 1 month return (Momentum 12-1), and the negative of past 3 years monthly volatility (Volatility 3Y). Each month the rank correlation is calculated and then averaged over the full sample. Results are estimated based on our Global universe and the sample period is January 1986 - December 2015.

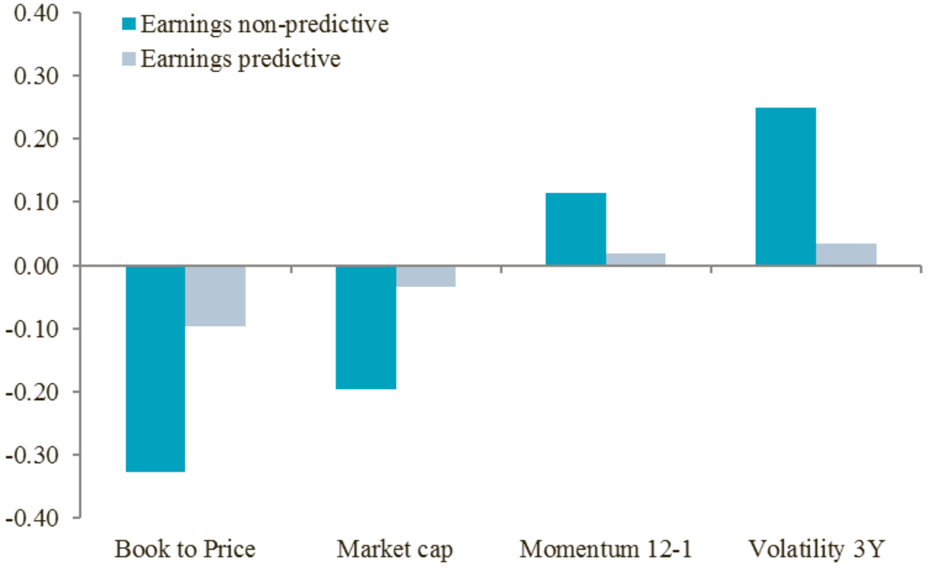


Figure 3.3 shows the average rank correlation between quality and value, size, momentum, and low volatility factor portfolios. Indeed we see that the 'earnings non-predictive' definition of quality is relatively highly correlated with low volatility due to explicitly including characteristics that focus on stability. At the same time, these stocks tend to be relatively more expensive as the rank correlation with book-to-price is negative. The higher price of 'quality' is not a new insight as it has been documented by Novy-Marx (2013) and Asness et al (2014). Both quality definitions show similar correlations with the other. However, the 'earnings predictive' quality is correlated to a much more limited extent making it a more independent factor. Its low rank correlation of 0.03 with low volatility shows that the defensive features of quality come indirectly as a

result of the strong underlying fundamentals and not by directly targeting low-volatile companies.

3.5. Conclusion

In this paper, we investigate a common set of accounting-based variables commonly referred to as measuring the quality of a firm and test their predictive power for future earnings growth and stock returns. We find that the predictive power of quality factors originates from its measures being good proxies for future earnings growth. Quality measures can predict future stock returns if and only if they are good proxies for future earnings growth. Quality variables that are no good proxies for future earnings growth have no predictive power for stock returns. The potential predictive power of quality measures for stock returns can be fully attributed to their predictive power for future earnings growth. We also analyze the robustness of the predictive power of quality for stock returns in an international and multi-asset setting: we investigate the predictive power of quality measures for future stock returns in both the U.S., Europe, Japan, emerging markets, and corporate bond markets. Our results are consistent across regions and asset classes – stocks and bonds issued by high-quality companies outperform those issued by low-quality companies if the quality measures used are good proxies for future earnings growth.

3.6. Appendix A:

3.6.1. A.1 Variable Definitions

In this section, we describe for each anomaly variable its detailed definition. We obtain the fundamental data, in order of preference, Compustat quarterly, Compustat annual, Worldscope quarterly, Worldscope semi-annual, Worldscope annual. To avoid a forward-looking bias, we lag Compustat data by three and Worldscope data by six months.

ROE is income before extraordinary items (*NI*) divided by book equity (*BE*).

$$ROE = \frac{NI_t}{BE_t}$$

Margins are defined as income before extraordinary items (*NI*) divided by sales (*SALES*).

$$Margins = \frac{NI_t}{SALES_t}$$

ROE growth is the 12-months difference in ROE as defined above.

$$\Delta ROE = ROE_t - ROE_{t-12}$$

Earnings variability is the standard deviation of y-o-y ROE growth over the last five years.

$$Earnings\ variability = \sqrt{\frac{1}{4}\sum_{y=0}^{-4}\left(\Delta ROE_y - \overline{\Delta ROE}\right)^2}$$

Leverage is calculated as total debt (*Debt*) to book equity (*BE*).

$$Leverage = \frac{Debt_t}{BE_t}$$

Accruals are defined as the change in operating working capital (ΔWC) minus depreciation, depletion and amortization (*Depr*)all deflated by total assets (*TA*). Thereby, operating working capital is current asset (*CA*) minus cash and short-term investments (*Cash*)minus changes in current liabilities (*CL*) plus short-term debt (*SD*)and taxes payable (*TP*) (both if available).

$$Accruals = \frac{\Delta WC_t - Depr_t}{TA_t}$$

$$WC_t = (CA_t - Cash_t) - (CL_t - SD_t - TP_t)$$

Investment is the ratio of total assets (*TA*) in month t to total assets in month t−12.

$$Investments = \frac{TA_t}{TA_{t-12}}$$

Gross profitability is defined as sales (*Sales*) minus cost of goods (*COGS*) sold both divided by total assets (*TA*).

$$Gross\ profitability = \frac{SALES_t - COGS_t}{TA_t}$$

3.6.2. Appendix B: Tables

Table 3.8: Predictive power of quality measures for three years future earnings growth

Table 3.8 reports the results of Fama-MacBeth (1973) regressions of future three-year growth in earnings scaled by book equity $\left(\frac{Earnings_{t+r} - Earnings_t}{BE_t}\right)$ on individual firm characteristics. Characteristics are calculated according to Appendix A and winsorized at 1% level. t-statistics are Newey-West adjusted using four lags. The last row shows the average adjusted R-squared. Regressions are run on quarterly data during the period January 1986 - December 2015 for our Global markets sample. Panel A shows results of univariate regressions, Panel B includes region dummies, and Panel C controls for other firm characteristics. Every column represents regressions for the respective quality measure, in brackets (+) or (-) is the expected sign of the coefficient.

	ROE	Margins	ROE growth	Leverage	Earnings variability	Gross profits	Accruals	Investments
	(+)	(+)	(+)	(-)	(-)	(+)	(-)	(-)
Panel A: Regressions of change in future earnings on quality variables (no controls)								
Intercept	7.59	5.57	3.08	1.80	2.72	3.13	2.35	4.65
	[7.35]	[5.15]	[3.19]	[2.27]	[3.14]	[2.55]	[2.38]	[4.85]
Quality measure	-38.77	-14.12	-37.46	2.51	0.46	2.48	-34.59	-16.00
	[-9.1]	[-10.35]	[-10.54]	[6.34]	[5.12]	[2.06]	[-8.25]	[-5.54]
R-sq	10.34	4.77	8.09	2.64	1.69	0.31	1.05	1.67
Panel B: Regressions of change in future earnings on quality variables (region dummies)								
Intercept	9.01	7.89	3.81	2.44	3.41	3.85	3.17	5.67
	[7.52]	[6.36]	[3.83]	[2.59]	[3.72]	[2.89]	[3.05]	[5.18]
Quality measure	-38.99	-15.43	-36.42	2.54	0.40	2.30	-31.44	-16.52
	[-8.6]	[-9.77]	[-10.34]	[6.57]	[5.06]	[2.28]	[-7.87]	[-6.20]
R-sq	12.20	6.99	9.60	4.66	3.38	2.34	2.81	3.55
Panel C: Regressions of change in future earnings on quality variables (with controls)								
Intercept	4.67	2.44	2.51	2.89	2.53	5.05	2.84	3.74
	[2.93]	[1.56]	[1.64]	[1.88]	[1.79]	[3.04]	[1.81]	[2.23]
Quality measure	-58.60	-17.71	-40.38	1.90	0.41	-4.65	-29.53	-18.74

Table 3.8 – cont'd

	[-16.60]	[-12.69]	[-12.23]	[5.06]	[5.07]	[-3.54]	[-8.71]	[-7.51]
ln(mcap)	-0.37	-0.21	-0.57	-0.73	-0.57	-0.76	-0.74	-0.62
	[-2.52]	[-1.41]	[-3.63]	[-4.30]	[-4.29]	[-5.05]	[-4.75]	[-3.69]
ln(Book-to-price)	-10.12	-6.00	-4.83	-4.22	-4.46	-5.50	-4.81	-5.32
	[-15.49]	[-12.34]	[-12.93]	[-11.76]	[-12.18]	[-10.76]	[-11.66]	[-12.44]
Momentum 12-1	7.46	9.20	10.08	9.68	8.60	8.79	9.07	8.77
	[6.09]	[8.94]	[9.60]	[9.58]	[8.43]	[9.10]	[9.43]	[8.58]
Beta 3Y	-1.19	-0.74	-0.09	0.37	0.06	0.33	0.34	0.32
	[-1.73]	[-1.11]	[-0.14]	[0.46]	[0.08]	[0.41]	[0.47]	[0.47]
R-sqt	22.96	12.75	15.20	8.73	7.95	7.42	7.66	8.69

Chapter 4

Factor Investing From Concept to Implementation*

4.1. Introduction

Mutual funds following factor investing strategies based on equity asset pricing anomalies, such as the small-cap, value, and momentum effects, earn significantly higher CAPM alphas than traditional actively managed mutual funds. This effect is unrelated to other fund characteristics like age, expenses, and turnover; is robust to a global sample of mutual funds and bootstrapped confidence intervals; and is stronger for funds that are exposed to multiple factors simultaneously. While excess returns earned by factor funds net of fees are significantly smaller than the theoretical premiums of the asset pricing anomalies, they are still positive and statistically and economically significant. For example, if an investor would randomly select a factor fund and would apply a buy-and-hold strategy, this investors would earn 110 basis points per annum in excess of the return that is earned by the average traditional actively managed mutual fund.

However, the actual returns that investors earn by investing in factor mutual funds appear to be significantly lower than this number because investors do not follow buy-and-hold strategies, but rather dynamically reallocate their funds both across factors and factor managers. By attempting

* This chapter is based on the paper Van Gelderen, Huij, and Kyosev (2019). The paper version of the chapter is published in the *Journal of Portfolio Management*

to time across factors, investors lose a large portion of the return they could earn with a buy-and-hold strategy.

To better understand how investors dynamically allocate to factor funds, we study the flow-performance relation for these funds. Although factor funds have attracted significant fund flows over our sample period, it appears that fund flows have been driven by factor funds earning high past returns and not by the funds providing factor exposures. Similar to Zheng (1999), we find very little evidence of a "smart money" effect in the sense that flows predict future fund performance. In fact, consistent with the recent findings of Cornell, Hsu, and Nanigian (2017) we do not observe a positive relationship between fund flows and future performance.

We argue that rather than timing factors and factor managers, investors would be better off by using a buy-and-hold strategy and selecting a multi-factor manager. For example, if an investor would randomly select a factor fund that is exposed to two factors simultaneously and would apply a buy-and-hold strategy, this investor would earn 190 basis points per annum in excess of the return that is earned by the average traditional actively managed mutual fund. Interestingly, an investor would earn This number would be 240 basis points per annum if the investor would have selected a manager that is exposed to three factors simultaneously, and even 270 basis points per annum if the manager would be exposed to 4 or more factors simultaneously.

Our study is closely related to the work of Van Gelderen and Huij (2014) who show that factor mutual funds earn significant excess returns using a large sample of U.S. equity mutual funds. We also extend the work of Dichev (2007) and Hsu (2016) who show that the actual return earned by investors in hedge funds and small-cap, value, and growth mutual funds are significantly lower than the returns they could earn with buy-and-hold strategies because they dynamically reallocate their funds across factors and factor managers.

Our main contributions are the following: first, the flow-performance analysis we perform helps better understand how investors allocate to factor funds; and second, our analyses of multi-factor strategies help investors harvest factor premiums more effectively. Other contributions of our study are the inclusion of the profitability and investments factors in our analyses; the use of global equity fund data next to U.S. equity fund data; and the use of the bootstrap approach put forward by Fama and French (2010) that has been designed to help differentiate between skill and luck when assessing mutual fund performance.

The remainder of the paper is organized as follows: Section 4.2 describes our data and methodology. Section 4.3 discusses our empirical results and Section 4.4 concludes.

4.2. Data and Methodology

4.2.1. Data

For our U.S. sample, we download monthly data from CRSP Survivorship Bias Free Mutual Fund Database. We use monthly returns, total assets values, quarterly turnover ratio, and expense ratio characteristics. Fund age is calculated as the sum of months with available observations and fund size is measured by its total assets. We adjust total net assets for mergers and acquisitions when calculating the fund inflows. Next, we adjust our mutual fund sample to domestic, equity, long-only funds by selecting the following objective codes: EI, EIEI, G, GI, I, LCCE, LSGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, SG. We use the return of the longest fund share class throughout our analysis. For robustness, in an unreported analysis, we also use value-weighted share classes and the share class with the highest total assets value - our conclusions remain intact. The sample period is from January 1990 to December 2015 and we only include funds with more than 36 available monthly return observations and CAPM R-squared values higher than 0.6, where the market return is downloaded from Kenneth French's data library. To limit incubation bias concerns we follow Fama and French (2010) and remove funds with total assets less than USD 5 million.

Our Global sample comprises of all Global Developed Markets equity long-only mutual funds in the Morningstar Database. Similar to our U.S. sample we restrict funds to only those with more than 36 return observations and CAPM R-squared values higher than 0.6. U.S. and Global markets factor returns are also downloaded from the Kenneth French data library. Due to factor return availability, we start our global sample one year later – from January 1991 to December 2015.

Table 4.1: Sample construction

The table shows summary statistics for our United States (U.S.) and Global samples. All Funds is the number of all mutual funds in our sample. Less than 36 obs. is the number of funds excluded due to having less than the selected minimum number of data points. R-squared < 0.6 is the number of funds excluded due to having CAPM R-squared less than 0.6. Remaining funds is the number of funds used for the analysis. Dead funds is defined as the number of funds with missing return values during the last month.

	U.S.	Global
Sample period	Jan. 1990 - Dec.2015	Jan. 1991 - Dec. 2015
All Funds	3,713	7,334
Less than 36 obs.	-396	-2,193
R squared < 0.6	-208	-282
Remaining	**3,109**	**4,859**
Dead	1,334	2,000
Alive	1,775	2,859

Table 4.1 shows a detailed summary of our sample construction process. For the U.S., our initial sample consists of 3,713 mutual funds. We remove 396 funds due to having less than 36 available observations available and 208 funds due to having CAPM R-squared values lower than 0.6. The remaining sample covers 3,109 funds out of which 1,334 are dead and 1,775 are alive. In total, we have 493,512 fund-month observations available. Our Global sample starts with 7,334 equity funds. We remove 2,193 funds due to having less than 36 return observations and 282 funds due to having CAPM R-squared values lower than 0.6. 2,000 dead funds and 2,859 alive funds remain for a total sample of 4,859 funds. In total, we have 670,099 fund-month observations available.

4.2.2. Methodology

Our empirical analyses consist of three main sections, respectively, evaluating the performance of factor fund managers; computing the actual returns earned by investors in factor funds, and investigating the flow-performance relation for factor funds.

4.2.3. Factor fund classification and performance evaluation

In the first empirical section of our paper, we investigate if mutual funds following factor investing strategies based on equity asset pricing anomalies, such as the small-cap, value, and momentum effects, earn higher alphas than traditional actively managed mutual funds. For these analyses we employ three statistical techniques: return-based style analysis to classify factor funds; cross-sectional regressions to evaluate the performance of factors funds, and bootstrap analyses to test the robustness of our results.

Our fund classification method closely follows the methodology employed by Van Gelderen and Huij (2014). We download monthly factor returns from Kenneth French's data library. For each fund, we run the 5-factor Fama and French model augmented with momentum using all available return observations

$$R_{i,t} = \alpha_i + \beta_i \cdot (R_{M,t} - R_{f,t}) + s_i \cdot SMB_t + h_i \cdot HML_t + w_i \cdot WML_t + r_i \cdot RMW_t + c_i \cdot CMA_t + \varepsilon_{i,t} \tag{4.1}$$

where $R_{i,t}$ is the excess return of mutual fund i in month t, $R_{f,t}$ is the risk-free return in period t, α_i is the alpha of fund i, $R_{M,t}$ is the return on the market portfolio in period t, *SMB, HML, WML, RMW,* and *CMA* are returns of long-short factor mimicking portfolios for the size, value, momentum, profitability, and investments factors, respectively. β, s, h, w, r, and c are the estimated fund specific factor coefficients, and $\varepsilon_{i,t}$ is the residual return of fund i in month t, under the assumption of iid. Similar to Van Gelderen and Huij (2014) we classify a fund as being a factor fund if the regression coefficient on the respective factor is positive and statistically significant. For example, if the SMB beta coefficient of fund i is higher than 2 we identify fund i as a small cap fund. A fund is considered to be a low-beta fund when its β is smaller than 0.8. Funds can have multiple factor fund classifications simultaneously.

To measure fund performance we use the intercept from the following one-factor model:

$$R_{i,t} = \alpha_i + \beta_i \cdot (R_{M,t} - R_{f,t}) + \varepsilon_{i,t} \tag{4.2}$$

We use CAPM alpha instead of the intercept from regression (1) as our main return performance as we want to measure the excess return coming from exposures to one of the six factors. Following Van Gelderen and Huij (2014) we limit the effect of outliers by calculating the z-score of fund alphas, winsorizing it at -2 and 2

$$z\_Alpha_i = min\left(2, max\left(-2, \frac{\alpha_i - \mu_\alpha}{\sigma_\alpha}\right)\right) \tag{4.3}$$

where α_i is the alpha of fund i from the one-factor model, μ_α is the average alpha across all funds in the sample, and σ_α is the cross sectional standard deviation of all fund alphas.

We use the following cross-sectional regression to evaluate the performance of factor funds:

$$z_{Alpha_i} = \alpha_i + b_1 \cdot Low\_beta + b_2 \cdot Smal\_cap + b_3 \cdot Value + b_4 \cdot Momentum + b_5 \cdot Profitability + b_6 \cdot Investments + \varepsilon_i \tag{4.4}$$

where *Low_beta, Small_cap, Value, Momentum, Profitability,* and *Investments* are 1 if the fund is classified as a low-beta, small cap, value, momentum, profitability, or investments factor fund, or 0 otherwise.

We also run an augmented version of this regression:

$$z\_Alpha_i = \alpha_i + b_1 \cdot Low_{beta} + b_2 \cdot Smal_{cap} + b_3 \cdot Value + b_4 \cdot Momentum + b_5 \cdot Profitability + b_6 \cdot Investments + b_7 \cdot \log age + b_8 \cdot \log size + b_{19} \cdot \exp_{\text{ratio}} + b_{10} \cdot turn_{ratio} + \varepsilon_i \tag{4.5}$$

where $\log age$ is the natural logarithm of fund age, calculated as the number of months with available return observations, $\log size$ is the natural logarithm of fund size, measured as its average total net assets, *exp_ratio* is the average total expense ratio, and *turn_ratio* is the average turnover ratio. In our Global markets sample, we do not include *exp_ratio*, and *turn_ratio* in our regressions due to the underlying data being unavailable.

To rigorously test the robustness of our results we employ a bootstrap method in the spirit of Fama and French (2010). In the distribution of active manager returns, we see that on average fund alpha is negative after cost with approximately the average cost level. This implies that funds on average produce alpha which is insufficient to cover the fees they charge. However, the fact that some managers tend to be on the positive side of the distribution might indicate that they have some level of skill or that they just generated high returns by chance. To control for this we do a bootstrap analysis where we simulate mutual fund alpha distribution with a true alpha equal to zero. To do so we simulate 5,000 cross-sectional zero-alpha distributions. First, we subtract the one-factor alpha from the returns of each fund to force its true alpha to zero. Second, at each run, we select a random number of months with replacement similar to Fama and French (2010). By selecting the same number of months for all funds we keep the cross-sectional properties of mutual fund performance which is directly related to the alpha distribution. Third, to control for difference in number of observations for each fund we compare their performance based on the *t*-statistic of alpha (t(α)) and not on alpha itself. After having 5,000 simulated t(α) we calculate our bootstrapped distribution by calculating the average t(α) at each percentile over all 5,000 runs. The resulting cross-sectional distribution has an implicit assumption that all managers have enough skills to cover their fees. As we know that the true alpha is zero that means that all alphas which are different from zero are observed by luck. As such, to infer that a manager has skills exceeding their fees the t(α) of the actual distribution should be higher than the simulated t(α) at a certain percentile.

4.2.4. Dollar-weighted returns

In the second empirical section of the paper we calculate the actual returns that investors earn by investing in factor funds and test if these returns are different from the return that a buy-and-hold investor would earn by randomly selecting a factor fund.

To calculate investors' returns we follow the methodology proposed by Dichev (2007) and estimate fund distributions (i.e, capital allocations to individual funds) in the following way:

$$distribution_{i,t} = (1 + r_t).TNA_{i,t-1} - (TNA_{i,t} + M_{i,t}) \tag{4.6}$$

where $TNA_{i,t}$ is the total net assets of fund i in month t, $TNA_{i,t-1}$ is the total net assets of fund i in month *t-1*, r_t is the return of fund i in month t, $M_{i,t}$ is the total growth in assets of fund i due to mergers and acquisitions in month t.

We then calculate dollar-weighted returns as the IRR with the negative of the first available TNA as the initial value; the last available TNA as terminal value; and the estimated distribution as monthly capital flows. We perform the main analysis at the aggregate factor level as we first sum all assets for each factor classification and then calculate distribution and IRR at the total asset level as in Dichev (2007) and Hsu (2016).

To test if the actual return investors earn by investing in factor funds is different from the return earned by randomly selecting a factor fund and applying a buy-and-hold strategy we perform a bootstrap analysis in which we keep the order of capital flows unchanged and randomly shuffle fund returns as in Dichev and Yu (2011).

4.2.5. Flow-performance relation

Finally, in the third empirical section of our study, we analyze the flow-performance relation for factor mutual funds to better understand how investors dynamically allocate to these funds. To this end, we regress fund flows on fund characteristics. Relative fund flows are calculated as the negative of monthly distribution divided by beginning of month total assets:

$$rel\_flow_{i,t} = \frac{TNA_{i,t} - (1 + r_t)TNA_{i,t-1} - M_{i,t}}{TNA_{i,t-1}} \tag{4.7}$$

We winsorize *rel_flow* at one percent to limit the impact of outliers. We then estimate the flow-performance relations using the following piecewise linear regression as in Sirri and Tufano (1998):

$$\begin{aligned} rel\_flow_{i,t} = {} & \alpha_i + b_1 \cdot Low\_beta + b_2 \cdot Smal\_cap + b_3 \cdot Value + b_4 \cdot Momentum + \\ & b_5 \cdot Profitability + b_6 \cdot Investments + b_7 \cdot \log age + b_8 \cdot \log size + b_9 \cdot \exp\_\mathrm{ratio} \cdot \\ & + b_{10} \cdot turn\_ratio + b_{11} \cdot Performance + b_{12} rank_{i,t-1}^{bottom} + b_{12} rank_{i,t-1}^{middle} + \\ & b_{12} rank_{i,t-1}^{top} + \varepsilon_i, \end{aligned} \tag{4.8}$$

where *Performance* refers to the past 12 month average outperformance over the market portfolio (or past 12 month CAPM alpha in some of our regression specifications) and top, middle, and bottom are calculated as follows

$$rank_{i,t}^{bottom} = \min(rank_{i,t}, 0.2)$$

$$rank_{i,t}^{middle} = \min(rank_{i,t} - rank_{i,t}^{bottom}, 0.6)$$

$$rank_{i,t}^{top} = \min\left(rank_{i,t} - rank_{i,t}^{bottom} - RANK_{i,t}^{middle}, 0.2\right)$$

Where $rank_{i,t}$ is the rank of fund i in month t based on the measure of past performance which is past 12 month outperformance or past 12 month CAPM alpha depending on the regression specification.

4.3. Empirical results

This section describes the results of our empirical analyses along three research questions (i) do factor premiums exist in mutual funds returns, (ii) do investors in factor funds successfully harvest factor premiums, and (iii) what drives the allocation decision of investors in mutual funds.

In the first section of our empirical analysis, we investigate if mutual funds following factor investing strategies earn higher alphas than traditional actively managed mutual funds. In the second section, we calculate what returns investors earn by investing in mutual funds that follow factor investing strategies and test if this return is different from the return that a buy-and-hold investor would obtain by randomly selecting a factor fund. Finally, in the third section, to better understand how investors dynamically allocate to these funds we study the flow-performance relation for factor mutual funds.

4.3.1. Do factor funds earn higher alphas?

In our first analyses, we consider the distribution of fund alphas for various fund classifications. Table 4.2 shows that factor funds earn significantly higher alphas than traditional actively managed mutual funds. Only 17 percent of the traditional actively managed mutual funds earn positive alphas after fees in the long run. This number is substantially larger for factor funds. For low-beta funds this number is 52 percent; for small-cap funds - 53 percent; for value funds - 52 percent; for momentum funds - 40 percent; for profitability funds - 57 percent; and for investments funds - 60 percent.

Table 4.2: Distribution of fund alphas

The table shows distributions of annualized fund alphas across all U.S. funds in the CRSP Mutual Fund Database with total assets above USD 5 mln. Alphas are calculated per fund as the intercept from CAPM regressions over all available observations during the sample period Jan. 1990 – Dec. 2015. '<-4' shows the percentage of funds with annualized alphas less than -4%, '-4:-2' shows the percentage of funds with annualized alphas between -2% and 4%, '%.0' shows the number of funds with positive alphas.

	<-4	-4:-2	-2:0	0:2	2:4	>4	% < 0	% > 0	# funds
All funds	9%	16%	34%	28%	9%	3%	59%	41%	3,109
No exposure	20%	28%	34%	13%	3%	1%	83%	17%	515
Low Beta	6%	11%	32%	42%	8%	1%	48%	52%	231
Small cap	7%	12%	28%	31%	16%	6%	47%	53%	1,404
Value	4%	12%	32%	33%	14%	5%	48%	52%	1,029
Momentum	8%	14%	37%	29%	8%	3%	60%	40%	781
Profitability	2%	9%	32%	37%	15%	4%	43%	57%	898
Investments	2%	8%	30%	43%	11%	5%	40%	60%	437

To test if differences in performance are statistically significant and independent, we perform regression analysis in which we regress fund performance on fund classifications. The results of this regression analysis are presented in Panel A of Table 4.3 and indicate that factor funds earn significantly higher alphas than traditional actively managed mutual funds. Specifically, when we consider the results in our most parsimonious specification (Table 4.3, Panel A, Regression 7), we find that funds with exposure to the low-beta, small cap, value, momentum, profitability, and investments factors have, respectively, 0.34, 0.48, 0.20, 0.12, 0.35, and 0.30 standard deviations higher alpha than traditional actively managed mutual funds. The *t*-values of these coefficient estimates are larger than 3 in all cases indicating that our results are statistically significant.

Table 4.3: Fund factor exposures and outperformance

The table shows univariate and multiple regression results of all U.S. funds during the sample period Jan. 1990 – Dec. 2015 in the CRSP Mutual Fund Database with total assets above USD 5 mln. Winsorized (at -2 and 2), Z-Score of CAPM alphas is regressed on dummies indicating funds belonging to a specific factor group. Ln(age) is the natural logarithm of fund's age, calculated as the number of months the fund has been in our sample. Ln(size) is the natural logarithm of average fund's total assets in U.S. dollars. exp_ratio and turn_ratio are the average expense ratio and turnover ratio per mutual fund in our sample.

	Reg 1	Reg2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7
Panel A: Style-performance relationship							
Intercept	0.01	-0.18	-0.11	0.01	-0.12	-0.04	-0.47
t-stat	[0.39]	[-9.00]	[-5.80]	[0.58]	[-6.83]	[-2.56]	[-18.37]
Low Beta	0.11						0.34
t-stat	[1.93]						[6.23]
Small cap		0.43					0.48
t-stat		[14.47]					[16.52]
Value			0.36				0.20
t-stat			[11.46]				[6.22]
Momentum				0.02			0.12
t-stat				[0.47]			[3.44]
Profitability					0.46		0.35
t-stat					[14.24]		[10.08]
Investment						0.40	0.30
t-stat						[9.20]	[6.84]
R-squared	0.1%	6.3%	4.0%	0.0%	6.1%	2.6%	16.3%

Table 3 cont'd

Panel B: Style-performance relationship controlling for fund specific characteristics

Intercept	-1.66	-1.52	-1.51	-1.64	-1.35	-1.56	-1.08
t-stat	[-11.68]	[-11.20]	[-10.65]	[-11.51]	[-9.33]	[-10.97]	[-7.85]
Low Beta	0.08						0.26
t-stat	[1.41]						[4.94]
Small cap		0.47					0.52
t-stat		[16.60]					[18.35]
Value			0.24				0.15
t-stat			[7.69]				[4.72]
Momentum				0.03			0.10
t-stat				[0.91]			[2.97]
Profitability					0.28		0.24
t-stat					[8.25]		[6.87]
Investment						0.22	0.25
t-stat						[5.33]	[5.96]
ln(age)	0.30	0.25	0.25	0.29	0.22	0.28	0.11
t-stat	[9.28]	[7.99]	[7.76]	[9.17]	[6.67]	[8.56]	[3.42]
ln(size)	0.10	0.09	0.09	0.09	0.09	0.09	0.09
t-stat	[8.48]	[8.67]	[8.36]	[8.40]	[8.37]	[8.22]	[8.78]
exp_ratio	-0.20	-0.25	-0.20	-0.21	-0.21	-0.21	-0.25
t-stat	[-6.59]	[-8.63]	[-6.50]	[-6.79]	[-6.86]	[-6.97]	[-8.75]
turn_ratio	-0.04	-0.07	-0.03	-0.05	-0.03	-0.03	-0.05
t-stat	[-2.21]	[-4.01]	[-1.63]	[-2.42]	[-1.43]	[-1.68]	[-2.87]
R-squared	15.6%	22.9%	17.3%	15.6%	17.5%	16.4%	27.5%

In Panel B of Table 4.3, we extend the analysis by controlling our regressions for fund characteristics such as fund age, size, total expense ratio, and turnover ratio. Our results appear to be robust to controlling for these fund characteristics as the coefficient estimates and their *t*-values remain very similar to our first results.

To further understand the effect of factor exposures on mutual fund performance we classify funds according to the number of factors they are exposed to, presented in Table 4.4. Groups are mutually exclusive and contain funds with significant loading to one, two, three, and four or more factors.

Results provide convincing evidence that a larger number of factor exposures lead to higher risk-adjusted mutual funds returns even after transaction costs

Table 4.4: Multifactor exposures and outperformance

The table shows multiple regression results of all U.S. funds during the sample period Jan. 1990 – Dec. 2015 in the CRSP Mutual Fund Database with total assets above USD 5 mln. Winsorized (at -2 and 2) Z-Score of CAPM alphas (z_alpha) is regressed on dummies indicating funds belonging to a specific factor group. Ln(age) is the natural logarithm of fund's age, calculated as the number of months the fund has been in our sample. Ln(size) is the natural logarithm of average fund's total assets in U.S. dollars. exp_ratio and turn_ratio are the average expense ratio and turnover ratio per mutual fund in our sample.

Dep. Variable:	z_alpha	z_alpha (controls)
Intercept	-0.49	-1.06
t-stat	[-14.10]	[-7.57]
1 factor	0.37	0.37
t-stat	[8.89]	[8.97]
2 factors	0.60	0.58
t-stat	[14.00]	[13.34]
3 factors	0.97	0.84
t-stat	[19.12]	[16.03]
>= 4 factors	1.36	1.18
t-stat	[16.49]	[14.71]
ln(age)		0.09
t-stat		[2.84]
ln(size)		0.09
t-stat		[8.71]
exp_ratio		-0.23
t-stat		[-7.95]
turn_ratio		-0.05
t-stat		[-2.73]
R-squared	14.8%	25.1%

and taxes are taken into account. The first column shows that funds with one, two, three, and four or more exposures have 0.37, 0.60, 0.97, and 1.36 standard deviations higher alpha than funds with no factor exposures.

Results remain intact after controlling for fund specific characteristics as shown in column 2.

i. Luck versus skill in mutual fund returns

In this section, we take a critical look at our previous findings. Fama and French (2010) show that, to a large extent, the performance of mutual funds can be attributed to luck. This is a strong and valid argument against the skill level of outperforming mutual funds as even if the true alpha is zero in specific periods, it can be higher or lower than zero just by chance. In the previous sections, we show that funds which incorporate academic insights in their investment process and provide exposure to proven factor premiums deliver higher net alpha relative to the control group. In this section, we take a more conservative approach and test whether the observed performance is above the one that could have been generated simply by chance.

Our simulated distribution of mutual fund returns possesses an important property that true net alpha is known to be zero which assumes that all managers have enough skills to cover for the fees they charge. If the actual distribution of fund returns is skewed to the left it shows that fund managers' skills do not cover for their expenses and on average mutual funds underperform the market portfolio. If the distribution is skewed to the right mutual funds have skills exceeding the fees they charge and generate added value for their investors.

Table 4.5 compares the distribution of fund alphas across all style groups to the simulated distribution. Consistent with Fama and French (2010) we show that in the right tail of the distribution managers have enough skill to deliver higher returns than their CAPM beta predicts. Specifically, at the 90^{th} percentile, the actual distribution has higher *t(a)* in 56% of the times compared to the 5,000 simulated runs.

Table 4.5: Fund factor exposures and outperformance after controlling for luck

The table shows actual fund performance over simulated performance for different percentiles. Performance is measured by the t-statistic of fund CAPM alpha *t(a)*. 'Simulated' is the average *t(a)* at the respective percentile over all 5,000 simulated runs. The remaining columns show the actual *t(a)* of the respective mutual fund style group. '%<act' is the percentage of runs out of all 5,000 runs with lower *t(a)* relative to the actual.

		Simulated	No exposure	Low Beta	Small cap	Value	Mom-entum	Profit-ability	Invest-ments
perc	5	-1.63	-3.22	-2.39	-1.80	-2.19	-2.15	-1.89	-1.59
%<act			0%	2%	27%	6%	7%	20%	49%
perc	25	-0.67	-2.04	-0.98	-0.61	-0.85	-1.06	-0.66	-0.51
%<act			0%	13%	56%	25%	8%	50%	71%
perc	50	0.01	-1.23	0.02	0.13	0.06	-0.23	0.18	0.28
%<act			0%	52%	69%	59%	17%	76%	86%
perc	80	0.85	-0.14	1.25	1.05	1.11	0.60	1.10	1.11
%<act			0%	91%	78%	83%	18%	82%	83%
perc	90	1.28	0.47	1.85	1.61	1.64	1.05	1.68	1.65
%<act			0%	96%	86%	88%	23%	89%	88%
perc	95	1.63	1.16	2.34	2.00	2.07	1.49	2.11	2.22
%<act			4%	97%	87%	90%	37%	92%	95%
perc	99	2.29	2.03	2.91	2.85	2.86	2.40	2.76	2.77
%<act			24%	95%	93%	93%	68%	90%	90%

At the 99th percentile this percentage increases to 84 with a *t(a)* of 2.63 compared to a simulated *t(a)* of 2.29 indicating that the returns of top-performing managers are significantly higher than the ones that could have been generated by luck even after adjusting for the fees they charge.

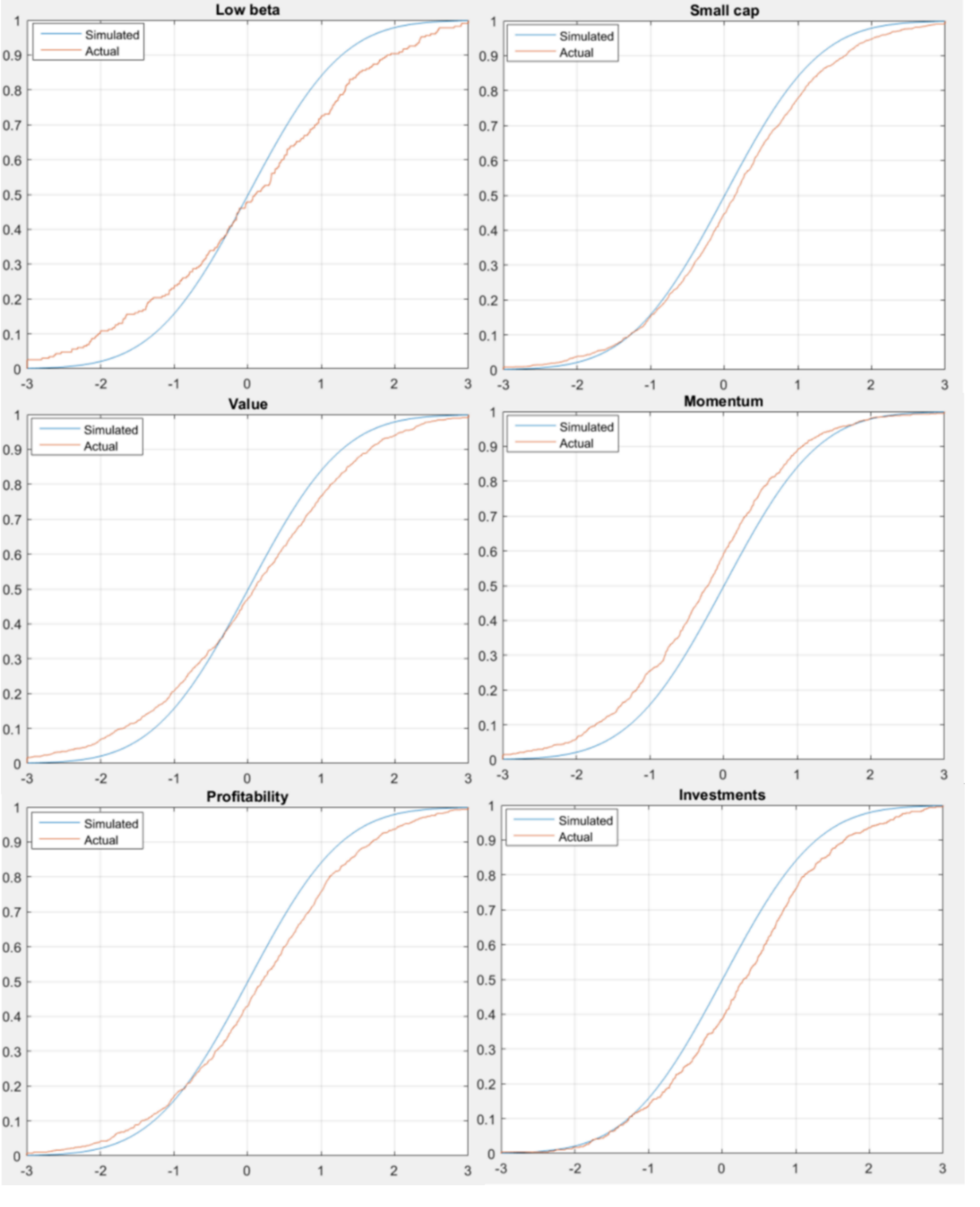
This picture significantly changes if we look at the control group 'No exposure'. Even at the 99th percentile *t(a)* is only 2.03 which is higher than a randomly simulated one in only 24% of the cases. This result indices that funds with no factor exposures systematically fail to deliver positive net alphas that cannot be attributed to luck. On the contrary, the net performance of all style groups does not seem to be attributable to chance. The net alphas of all groups (except momentum) are significantly higher relative to those based on our simulated distribution at most of the percentile levels. Namely, low beta and value funds generate positive luck-adjusted net returns in 50% of the cases, small cap, profitability, and investments – in 75% of the cases. Momentum produces positive luck adjusted returns only in the top 1 percentile which might be a result of the higher turnover and total costs of momentum managers.

These results strengthen the previously documented positive performance of factor investing funds as they show that they are much more robust surviving even the most conservative tests of our bootstrapping method. Further, the newly documented profitability and investments factors seem to be at least equally robust to the long known value, size, and low-risk premiums.

In Figure 4.1 we graphically show the cumulative density function of funds with low beta, small cap, value, momentum, profitability, and investments exposures. The horizontal axis shows the value of *t(a)* and the vertical axis – percentile values. The percentile at which the actual line is below the simulated line indicates that from this percentile onwards fund managers from the respective group generate net benchmark-adjusted returns beyond what can be expected by chance.

Figure 4.1: Simulated and actual cumulative density function of CAPM t(α) factor funds

The figure shows the cumulative density function of actual fund performance over simulated performance. Performance is measured by the *t*-statistic of fund CAPM alpha *t(α)*. 'Simulated' is the average *t(α)* at the respective percentile over all 5,000 simulated runs.



ii. Global Markets

To extend the scope of our research we conduct our main analysis on a Global Markets universe including long-only equity mutual funds from all developed countries. In Table 4.6 we show the distribution of fund alphas. It strengthens the conclusions of our U.S. analysis as all groups of factor funds have a higher probability of earning a positive alpha compared to traditionally active global mutual funds.

In Panel A of Table 4.7, we show that our U.S. results spill over to global markets. Funds belonging to all our style groups – low beta, size, value, momentum, profitability, and investments – deliver higher beta-adjusted returns compared to the average mutual fund. Results for the momentum factor stand out as, unlike in the U.S universe, momentum managers have 0.21 (t-stat of 6.37) standard deviations higher alpha than non-momentum funds. These results are not explained by controlling for other style exposures. In our regression specification 7 where we include all style dummies simultaneously, we see that except for value (t-stat of 1.38) all factor funds have significantly higher alphas than funds with no factor exposure. In our regression specification 7 where we include all style dummies simultaneously, we see that except for value (t-stat of 1.38) all factor funds have significantly higher alphas than funds with no factor exposure.

Table 4.6: Distribution of fund alphas – Global markets

The table shows distribution of annualized fund alphas across all Global Developed Markets funds in Morningstar Mutual Fund Database with total assets above USD 5 mln. Alphas are calculated per fund as the intercept from CAPM regressions over all available observation during the sample period Jan. 1991 – Dec. 2015. '<-4' shows the percentage of funds with annualized alphas less than -4%, '-4:-2' shows the percentage of funds with annualized alphas between -2% and 4%, '%>0' shows the number of funds with positive alphas.

	<-4	-4:-2	-2:0	0:2	2:4	>4	% < 0	% > 0	# funds
All funds	26%	30%	27%	12%	4%	2%	83%	17%	4,859
No exposure	34%	30%	24%	8%	2%	1%	88%	12%	1,858
Low Beta	22%	20%	26%	19%	7%	6%	68%	32%	142
Small cap	20%	28%	28%	15%	6%	3%	76%	24%	1,419
Value	23%	24%	28%	19%	6%	1%	74%	26%	514
Momentum	17%	32%	30%	16%	4%	2%	79%	21%	909
Profitability	15%	31%	32%	16%	5%	2%	77%	23%	1,283
Investments	15%	30%	25%	22%	5%	4%	70%	30%	304

Table 4.7: Factor exposures and outperformance – Global markets

The table shows univariate and multiple regression results of all Global Developed Markets funds during the sample period Jan. 1991 – Dec. 2015 in the Morningstar Mutual Fund Database with total assets above USD 5 mln. Winsorized (at -2 and 2) Z-Score of CAPM alphas is regressed on dummies indicating funds belonging to a specific factor group. Ln(age) is the natural logarithm of fund's age, calculated as the number of months the fund has been in our sample. Ln(size) is the natural logarithm of average fund's total assets in U.S. dollars.

	Reg 1	Reg2	Reg 3	Reg 4	Reg 5	Reg 6	Reg 7
Panel A: Style-performance relationship							
Intercept	0.01	-0.05	0.00	-0.02	-0.06	-0.01	-0.19
t-stat	[0.65]	[-3.42]	[0.14]	[-1.53]	[-4.19]	[-0.39]	[-10.63]
Low Beta	0.30						0.35
t-stat	[4.01]						[4.70]
Small cap		0.24					0.18
t-stat		[8.44]					[6.36]
Value			0.15				0.06
t-stat			[3.49]				[1.38]
Momentum				0.21			0.25
t-stat				[6.37]			[7.76]
Profitability					0.30		0.26
t-stat					[10.44]		[8.82]
Investment						0.36	0.36
t-stat						[6.82]	[6.97]
R-squared	0.3%	1.4%	0.2%	0.8%	2.2%	0.9%	0.0%

Table 7 cont'd

Panel B: Style-performance relationship controlling for fund specific characteristics

Intercept	-3.56	-3.42	-3.50	-3.43	-3.35	-3.44	-3.33
t-stat	[-22.20]	[-21.25]	[-21.45]	[-21.39]	[-20.68]	[-21.49]	[-20.25]
Low Beta	0.41						0.40
t-stat	[5.48]						[5.43]
Small cap		0.12					0.11
t-stat		[4.15]					[3.81]
Value			-0.03				-0.07
t-stat			[-0.77]				[-1.65]
Momentum				0.13			0.17
t-stat				[4.06]			[5.29]
Profitability					0.13		0.13
t-stat					[4.64]		[4.44]
Investment						0.28	0.28
t-stat						[5.42]	[5.57]
ln(age)	0.31	0.28	0.30	0.29	0.28	0.30	0.25
t-stat	[13.10]	[11.24]	[12.65]	[11.92]	[11.43]	[12.64]	[9.90]
ln(size)	0.12	0.12	0.12	0.12	0.11	0.11	0.11
t-stat	[13.93]	[13.89]	[13.71]	[13.74]	[13.39]	[13.40]	[13.56]
R-squared	10.8%	10.6%	10.2%	10.6%	10.7%	10.8%	12.6%

Panel B extends the analysis by controlling for fund specific characteristics and shows that the superior performance of factor funds cannot be attributed to their age or size. Only the coefficient on our value group becomes negative but insignificant (t-stat -0.77). On the other hand, momentum results remain robust indicating that despite the higher turnover the momentum premium can be harvested in practice. The newly documented factors profitability and investments seem to be some of the strongest factors as their coefficients remain positive and highly significant in all our tests.

4.3.2. Do investors in factor funds successfully harvest factor premiums?

In the previous section of the paper, we provide evidence that factor premiums survive even the most robust research specifications and that mutual fund managers seem to be able to harvest these premiums. However, the actual returns that investors earn by investing in factor mutual funds appear to be significantly lower because investors do not seem to follow buy-and-hold strategies but, rather, dynamically reallocate their funds both across factors and factor managers. By attempting to time across factors investors lose a large portion of the return they could earn with a buy-and-hold strategy and in this section, we quantify this loss. To do so we calculate the magnitude of factor premiums in three settings gradually reducing the level of abstraction. First, we calculate the long-only premiums of Fama and French (2015) and the low beta factors. Second, we calculate the return of mutual funds with exposure to these factors. Finally, we estimate the returns realized by investors in these funds. This analysis extends the one of Hsu (2016) who shows that investors in value and small-cap funds have underperformed S&P 500 while the value and small-cap funds themselves have outperformed the benchmark.

Table 4.8 describes the main results of this section. For each factor group we show the return of the long-only academic factor return, equally- and value-weighted mutual fund returns, and dollar-weighted returns at an aggregation level per factor. Starting with the first column we see that the market portfolio has earned a buy-and-hold return of 10.1% per annum compared to 9.6% for the average mutual fund. Moving from top to bottom in the table reduces the level of abstraction in calculating returns and gets closer in approximating the return to the end investors. A value-weighted return of 9.2% implies that larger mutual funds have generated lower returns than their small counterparts consistent with studies such as Chen et al (2004). Next, we calculate the dollar-weighted return on an aggregated level by summing up the dollar amount of all assets and calculating the internal rate of return according to the methodology proposed by Dichev (2007). The resulting return of 7.9% per annum captures the amount of equity timing or fund flowing in and out of our sample of US long-only domestic equity funds. For example, if a fund has strong returns in the first year of its existence but very low asset base, very few investors benefit from it.

Table 4.8: Mutual fund return versus investor returns

The table shows returns of all U.S. funds during the sample period Jan. 1991 – Dec. 2015 in the CRSP Mutual Fund Database with total assets above USD 5 mln. EW is the equally weighted, geometrically calculated, annualized return, VW is the total assets weighted, geometrically calculated, annualized return. Dollar weighted is the geometrically annualized internal rate of return (IRR), or the rate of return that makes the sum of discounted ending total assets and the present value of monthly distributions equal(?) to the initial total assets. The IRR calculation is done per factor level. It calculates IRR on an aggregate level as distributions are calculated based on the sum of all assets per fund style and value weighted fund returns in the same style group. Value, Momentum, Profitability, and Investments are based on 6 portfolios sorts as the average of small attractive and big attractive portfolio. For example, Value is the average of small value and big value portfolios. Size is the average of the small value, small growth, and small middle portfolio based on 6 size-value sorted portfolios. Low beta is the lowest quintile based on past market beta sort.

	All Funds	No exposure	Low beta	Size	Value	Momentum	Profitability	Investments
(a) Fama and French	10.1%		9.4%	12.4%	12.8%	14.9%	13.5%	13.1%
(b) Mutual Funds (Buy-and-hold) EW	9.6%	8.0%	7.5%	10.7%	9.9%	10.0%	10.0%	9.6%
(c) Mutual Funds (Buy-and-hold) VW	9.2%	7.6%	8.8%	10.1%	9.7%	9.2%	9.6%	9.4%
(d) Mutual Funds (Dollar weighted) per factor	7.9%	6.3%	7.5%	8.2%	8.7%	7.0%	8.7%	8.8%
difference (d) - (b)	-1.7%	-1.7%	0.1%	-2.5%	-1.2%	-3.0%	-1.3%	-0.7%
p-value difference	0.012	0.014	0.984	0.008	0.028	0.009	0.031	0.060

If later due to its good performance it attracts flows but subsequent returns are lower, the return of the fund will be higher than the return of the investors in this fund over the sample period.

The remaining columns of Table 4.8 show the same analysis per different group of funds. Row (d) shows that size, value, momentum, profitability, and investments fund investors lose respectively 2.5%, 1.2%, 3.0%, 1.3%, and 0.7% due to factor timing. The highest loss is incurred by investors in momentum funds. A possible reason is the intrinsic trend following nature of momentum which stimulates investors to allocate to momentum funds after a period of good performance which lowers their subsequent realized returns compared to the fund returns.

Our results have strong implications for mutual fund investors. Even though factor funds deliver positive alpha their investors have not been able to capture it due to their allocation decisions. For example, if investors believe in the value and momentum premiums but they only invest in value or momentum funds after a period of strong performance they lose a significant portion of the factor premium due to cyclicality in factor returns. A potential solution would be to buy both funds and hold on to them instead of moving assets across them.

Table 4.9 shows the annualized returns of funds with one, two, three, and four or more factor exposures. The average buy-and-hold investor would have earned 9.1%, 9.9%, 10.3%, and 10.6% compared to 8.0% of funds with no factor exposures. Similar to the single factor funds, the dollar-weighted returns of 7.4%, 7.6%, 8.9%, and 8.9% are lower than the time-weighted returns for the same group of funds, indicating that even if investing in multi-factor funds investors still make allocation decision which cost them a significant portion of the performance.

Figure 4.2 graphically illustrates our main points. The bars represent the return premium over traditionally actively managed mutual funds or 'no exposure' funds. The average academic long-only factor of Fama and French (2015) outperforms our control group with 4.7% per annum. The second bar shows the return of mutual funds with one-factor exposure. It is based on net asset values and as such includes the negative effect of taxes and trading costs on returns. This brings down the premium to 1.1% which is the return generated by investors invested in this group of funds at the beginning of our sample and holding on to the investment until the end of the sample. However, investors often make active allocation decisions based on their views on which factor is

Table 4.9: Multi-factor mutual fund returns and investor returns

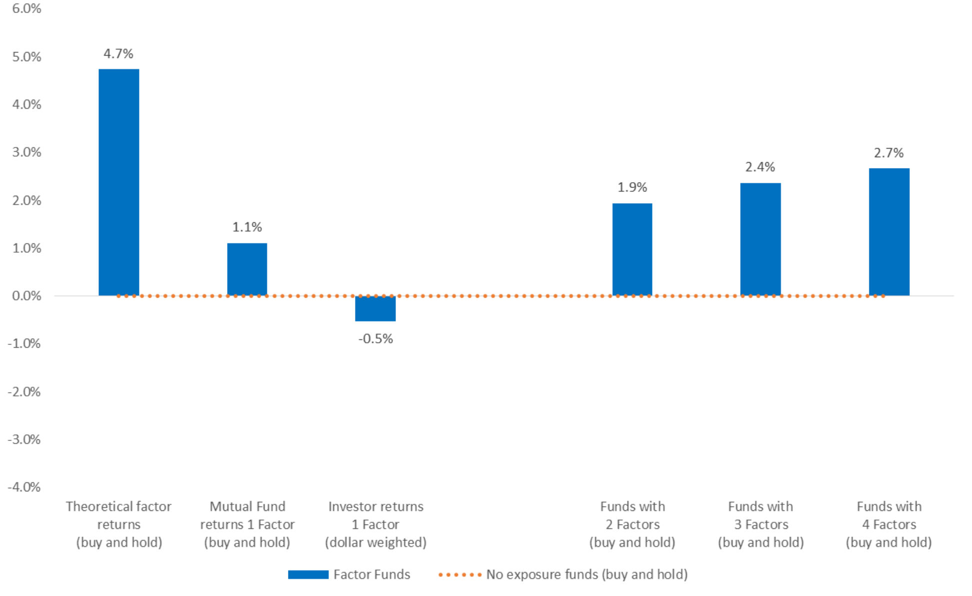
The table shows returns of all U.S. funds during the sample period Jan. 1991 – Dec. 2015 in the CRSP Mutual Fund Database with total assets above USD 5 mln. EW is the equally weighted, geometrically calculated, annualized return, VW is the total assets weighted, geometrically calculated, annualized return. Dollar-weighted is the geometrically annualized internal rate of return (IRR), or the rate of return that makes the sum of discounted ending total assets and the present value of monthly distributions equal to the initial total assets. The IRR calculation is done per factor level. It calculates IRR on an aggregate level as distributions are calculated based on the sum of all assets per fund style and value-weighted fund returns in the same style group.

	No exposure	1 factor	2 factors	3 factors	4+ factors
(a) Mutual Funds (Buy-and-hold) EW	8.0%	9.1%	9.9%	10.3%	10.6%
(b) Mutual Funds (Buy-and-hold) VW	7.6%	9.4%	9.0%	9.8%	10.0%
(c) Mutual Funds (Dollar weighted) per factor	6.3%	7.4%	7.6%	8.9%	8.9%
difference (c) - (a)	-1.7%	-1.6%	-2.3%	-1.4%	-1.8%
p-value difference	0.014	0.002	0.11	0.048	0.033

going to outperform going forward. The third bar incorporates the effect of these decisions on returns. It appears that despite one-factor mutual funds having a sizeable return premium of 1.1% over traditionally actively managed mutual funds the investors in those same funds underperform the control group with 0.5% due to poor timing decisions. The right three bars of the figure present what could have been the returns of investors if they allocated to funds with two, three, or four factors and holding on to them instead of timing across factors. The buy and hold premium is 1.9%. 2.4%, and 2.7% respectively.

Figure 4.2: Outperformance over traditional actively managed mutual funds

The figure shows returns of all U.S. funds during the sample period Jan. 1991 – Dec. 2015 in the CRSP Mutual Fund Database with total assets above USD 5 mln. Mutual fund returns are equally weighted, geometrically calculated, annualized returns. Investor returns are dollar-weighted geometrically annualized internal rate of return (IRR), or the rate of return that makes the sum of discounted ending total assets and the present value of monthly distributions equal to the initial total assets. The IRR calculation is done per factor level. It calculates IRR on an aggregate level as distributions are calculated based on the sum of all assets per fund style and value-weighted fund returns in the same style group. Styles are funds with one, two, three or four or more factor exposures. Theoretical return is the average long-only Fama and French (2015) factor returns and the lowest quantile based on low beta sorts. Value, momentum, profitability, and investments are based on six portfolios sorts as the average of small attractive and big attractive portfolio. For example, Value is the average of small value and big value portfolios. Size is the average of the small value, small growth, and small middle portfolio based on six size-value sorted portfolios. Low beta is the lowest quintile based on past market beta sorts.



4.3.3. What drives allocation decisions of mutual fund investors?

In this section, we unveil the drivers behind investor allocation decisions. This is crucial in having a full understanding of why investors consistently lose returns even when selecting the right funds. The natural starting point is to follow the insights of Sirri and Tufano (1998) who show that due to the complexity of having a full understanding into the methodology of each strategy investors just buy the ones with high past returns, assuming that past returns proxy accurately for manager skills. We follow their piecewise linear regression specification to control for the different degree of sensitivity of flows to performance in the tails of the performance distribution.

Our paper exhibits convincing evidence that funds exposed to factors outperform in the long-term and investors who strategically allocate to them can benefit from those premiums. As such, we test the hypothesis of whether investors allocate to factor funds strategically or just end up being invested in factor funds because of their good past performance. Towards this goal, we extend, the Sirri and Tufano (1998) flow-performance model with dummies indicating if funds belong to a specific factor group.

Table 4.10 contains the main results of this section. In regression 1 we show that relative flows are significantly higher for funds with high past twelve-month outperformance over the market (coefficient of 0.02 with t-stat of 12.02). This effect is highly non-linear as the top (bottom) group has a significant coefficient of 0.04 (-0.03), meaning that funds belonging to this group exhibit abnormally high (low) flows. Most importantly, it seems that past performance is the main driver of investor decisions. The coefficients on size, value, and momentum dummies are negative indicating that investors tend to avoid those funds. The coefficient on profitability is insignificant and only the coefficients on low beta and investments are positive and significant showing that investors invest in low-beta and investments funds more than what their past twelve-month returns suggest. In regression 2 we extend the analysis and test whether the allocation based on past returns are good timing decision in terms of future returns. As such, we include the future twelve-month returns in the equation. The coefficient on future performance is virtually zero (0.00 with a t-statistic 0.09) meaning that investing in funds with high past performance has no predictive power for future performance. In regression 3 we substitute past return with past CAPM alpha and results remain intact. The only difference is that the positive coefficient on the low beta dummy becomes zero indicating that investors allocate to low beta funds just as much as their past alpha implies.

Table 4.10: Flow performance relationship

The table shows Fama Macbeth (1773) multiple regression results of all U.S. funds during the sample period Jan. 1991 – Dec. 2015 in the CRSP Mutual Fund Database. Each month relative fund flows are regressed on dummies indicating funds belonging to a specific factor group and measures on performance. Ln(age) is the natural logarithm of fund's age, calculated as the number of months the fund has been in our sample at each point in time. Ln(size) is the natural logarithm of most recent fund's total assets in U.S. dollars, exp_ratio and turn_ratio are the most recent expense ratio and turnover ratio per mutual fund at each point in time. Presented coefficients are the average coefficients over the full sample and *t*-statistics are calculated as in Fama Macbeth (1973).

	Reg 1 12M outperformance	Reg 2 12M outperformance	Reg 3 12M alpha	Reg 4 12M alpha
intercept	0.05	0.05	0.05	0.05
	[16.87]	[16.90]	[19.13]	[20.23]
low beta	0.0046	0.0042	0.0001	-0.0001
	[8.37]	[7.77]	[0.16]	[-0.37]
size	-0.0013	-0.0013	-0.0003	-0.0006
	[-3.56]	[-3.50]	[-0.71]	[-1.45]
value	-0.0004	-0.0005	-0.0009	-0.0009
	[-1.07]	[-1.49]	[-2.75]	[-2.59]
momentum	-0.0022	-0.0021	-0.0012	-0.0015
	[-7.01]	[-6.58]	[-3.73]	[-4.63]
profitability	0.0005	0.0001	0.0007	0.0003
	[1.88]	[0.60]	[2.72]	[1.34]
investments	0.0009	0.0008	0.0007	0.0007
	[2.96]	[2.73]	[2.09]	[2.13]
ln(age)	-0.0081	-0.0080	-0.0080	-0.0080
	[-36.87]	[-36.80]	[-37.08]	[-37.45]
ln(size)	0.0005	0.0004	0.0007	0.0003
	[6.51]	[5.72]	[8.00]	[3.74]
exp_ratio	-0.0025	-0.0025	-0.0023	-0.0024
	[-8.29]	[-8.36]	[-7.54]	[-8.10]
turn_ratio	0.0009	0.0009	0.0012	0.0012
	[2.50]	[2.54]	[3.24]	[3.31]

Table 4.10 cont'd

past performance	0.0224	0.0221	0.0224	0.0234
	[12.02]	[11.96]	[14.55]	[13.87]
bottom	-0.0319	-0.0314	-0.0339	-0.0380
	[-4.30]	[-4.26]	[-4.75]	[-5.10]
middle	-0.0018	-0.0014	-0.0042	-0.0054
	[-0.74]	[-0.58]	[-2.02]	[-2.50]
top	0.0438	0.0468	0.0349	0.0325
	[4.56]	[4.91]	[4.59]	[4.19]
future performance		0.0000		0.0006
		[0.09]		[2.28]
R-squared	0.092	0.093	0.089	0.091

This section presents evidence that fund flows have been driven by factor funds earning high past returns and not by the funds providing factor exposures. Consistent with Zheng (1999), we find very little evidence of a "smart money" effect in the sense that flows predict future fund performance. Instead of strategically allocating to factor premiums investors seem to avoid them and only allocate to factor funds if their performance has been good. This combined with the poor predictive power of flows to future returns indicates that investors indeed time poorly as proposed by Hsu (2016). This, in turn, explains the observed effect that investor returns are lower than funds returns. As such, investor behavior has important implications for the reasons why factor premiums continue to exist.

4.4. Conclusions

Mutual funds following factor investing strategies based on equity asset pricing anomalies such as the small-cap, value, momentum, profitability and investments effects earn significantly higher alphas than traditional actively managed mutual funds. A buy-and-hold strategy for a random factor fund would yield 110 basis points per annum in excess of the return earned by the average traditionally actively managed mutual fund. However, the actual returns that investors earn by investing in factor mutual funds appear to be significantly lower than this number because investors dynamically reallocate their funds both across factors and factor managers. Although factor funds have attracted significant fund flows over our sample period, it appears that investor fund flows have been driven by factor funds earning high past returns and not by the funds providing factor exposures. We argue that rather than timing factors and factor managers, investors would be better off by using a buy-and-hold strategy and selecting a multi-factor manager.

Chapter 5

Conclusions

This dissertation combines studies in the area of empirical asset pricing, addressing the big questions with regard to factor investing. Namely, we focus on the implications of factor investing on the efficiency of financial markets, the underlying drivers of factor premiums, the way factor investing strategies are implemented, and most importantly the added value for the end investors.

In the first chapter of the thesis, we start by identifying the global trends in academic research in finance and their contributions to the recent growth in factor investing. We present a detailed literature overview of market efficiency, theoretical asset pricing, empirical asset pricing, the source of factor premiums, and finally the events leading to the growth of factor investing. In a nutshell, each stream of literature has led to a long-lasting trend in the investment industry. Theoretical asset pricing, through the Capital Asset Pricing Model, inspired the concept of getting a low-cost exposure to the broad market portfolio. This sets the beginning of passive investing which currently comprises around 40% of all mutual fund assets. Empirical asset pricing identified a number of persistent factor premiums which can explain about 70% of the remaining active return of long-only mutual funds. After similar numbers were shown by Ang, Goetzmann, and Schaefer (2009), specifically for the performance of the Norwegian reserve fund, factor investing began to gain broader popularity in the investment industry. This thesis shows that from 2009 to 2018 the number of funds engaging in global equity multi-factor strategies tripled and the assets under management increased from under 2 billion to around 25 billion, mainly driven by new investor flows. All factor investing mutual fund assets in the U.S. and Global markets grew to about 250 billion U.S. Dollars by August 2018. We put these numbers in the context of passive investing growth over the years and show that the recent growth of factor investing resembles the initial growth of passive investing in the 1990s. As such, factor investing has a long way to go until it reaches the mature state of passive investing. Most importantly, both trends highlight the importance of academic studies for the investment industry and their continually evolving interrelationship.

In the second chapter, we contribute to the fundamental stream of literature on market efficiency. Understanding the source of factor premiums is crucial both for academic theories as well as for designing investment strategies. In this chapter, we propose a new information free-event of supply shocks in factor index rebalancing. Previous literature has been concentrated around large block sales and changes in S&P 500 index constituents, but these events have been shown to contain information about the future earnings potential of companies. We show that there is no link between factor index additions and deletions and improved earnings expectations. This allows us to attribute the documented abnormal returns to an exogenous shift in demand. The abnormal return for new additions (deletions) between announcement and effective day is 1.07% (-0.91%) as 0.73 (-0.42) percentage points of it persist after 3 weeks following the effective day. Similar pattern is seen for abnormal volume as at the effective day it is 74% (46) for additions (deletions). We document a direct relationship between abnormal returns and our proxy for the trading coming from index funds which seem to wait until the last day before adjusting their portfolio. Finally, we calculate the price of transparency for public factor indices to be 16.5 bps per annum which is a direct loss to index fund investors. This amount can also be interpreted as hidden costs to investors in index funds aiming to replicate the performance of factor indices. Our findings should serve as a call for action for asset owners and regulators who should carefully assess the consequences arising from the active nature of factor indices.

In chapter 3 we focus on the most recently documented quality factor. A number of existing studies aim to provide alternative definitions to this factor, but none of them is focused on identifying a clear framework in defining it. In the chapter, we investigate a common set of quality factors and test their predictive power for future earnings growth and stock returns. We find that the predictive power of quality factors originates from its measures being good proxies for future earnings growth. Quality measures can predict future stock returns if and only if they are good proxies for future earnings growth. Quality variables that are not good proxies for future earnings growth have no predictive power for stock returns. The potential predictive power of quality measures for stock returns can be fully attributed to their predictive power for future earnings growth. We also analyze the robustness of the predictive power of quality for stock returns in an international and multi-asset setting: we investigate the predictive power of quality measures for future stock returns in both the U.S., Europe, Japan, emerging markets, and corporate bond markets. Our results are consistent across regions, and asset classes – stocks and bonds issued by high-quality companies outperform those issued by low-quality companies if the quality measures used are good proxies for future earnings growth. These results contribute to the academic stream of literature by providing compelling evidence on the driver of the premium. On the other hand, they help investment professionals in defining better quality strategies by avoiding unrewarded features such as negative mean reversion in earnings.

Knowledge is the best asset anyone can have but only if used properly. Academic studies present compelling evidence on the persistence of factor premiums. Furthermore, mutual funds with exposure to these factors tend to have higher probabilities for outperforming their benchmarks. However, none of these facts means that society has benefited from the existence of factor premiums. This can only be the case if the end investors have been able to harvest those premiums. In the final chapter, we show that mutual funds following factor investing strategies based on equity asset pricing anomalies such as the small-cap, value, momentum, profitability and investments effects earn significantly higher alphas than traditional actively managed mutual funds. A buy-and-hold strategy for a random factor fund would yield 110 basis points per annum in excess of the return earned by the average traditionally actively managed mutual fund. However, the actual returns that investors earn by investing in factor mutual funds appear to be significantly lower than this number because investors dynamically reallocate their funds both across factors and factor managers. Although factor funds have attracted significant fund flows over our sample period, it appears that investor fund flows have been driven by factor funds earning high past returns and not by the funds providing factor exposures. This finding shows that in their search for higher returns investors have been systematically making the wrong timing calls. Even in the cases when they have selected the right funds on average, their poor allocation decisions have outweighed the positive fund selection in terms of generating a positive active return. We advocate that rather than timing factors and factor managers, investors would be better off by using a buy-and-hold strategy and selecting a multi-factor manager. In this case, investors' positioning would be in line with academic evidence increasing the probability of generating positive risk-adjusted returns in the long-term.

Next, to the academic contributions, this thesis has some important practical implications.

Factor indices have become increasingly popular due to their full transparency, simple rules-based methodology, and low costs. As such, they are largely regarded as passive by practitioners. However, they are active in nature due to the higher turnover embedded in their methodologies. This makes implementation especially important, and chapter 2 focuses on it by looking at price impact of index changes around rebalancing. We find a direct loss to investors in public factor indices of 16.5 basis points which can be seen as an additional shadow price. The short-term solution is that index fund managers buy new additions right after the announcement day despite the additional tracking error coming from it. However, if all managers do it the added value will disappear as the whole adverse price movement will be concentrated on the announcement day. Furthermore, in the current setup managers are not motivated to do it as they are benchmarked versus the factor index. As such, even if prices move against them, as long as they lose less than the index, they can report an outperformance. We advocate that asset owners and regulators impose a new benchmark for index fund managers – the pro forma index. The pro-forma index assumes all index changes are effective at the announcement day and not at the effective day, incorporating all trading related adverse price movements. This serves as a better benchmark as exact trading costs can be estimated by simply taking the difference in performance of the index fund and the pro-forma index during the rebalancing period. The resulting transparency will facilitate asset owners in assessing the exact added value of their managers and regulators in eliminating all potential conflict of interests between index providers, index fund managers, and asset owners.

The quality factor is the latest factor to be widely adopted in the industry. It is typically defined by accounting-based variables, most pronounced of which are profitability and investments as in Fama and French (2015). Due to the rather vague terminology, the variables used to define quality are highly dispersed. In chapter 3 we provide direct guidance to asset managers on how to definite the quality factor. Specifically, we show that the common driver of all quality definitions is that they predict future earnings growth. Once we control for it the predictive power of quality is fully explained. As such, our study suggests that it is not the exact variables used that differentiate good from bad quality definitions. Instead, a good quality definition is one that predicts future earnings growth and the individual variables are just a means of achieving this.

This thesis highlights the added value factor premiums have for investors. However, as long as investors do not efficiently harvest them the added value that academic insights have on society is limited. In chapter 4 we show that mutual funds with positive factor exposures exhibit a significantly higher probability of outperforming their benchmarks. However, despite that on average they delivered outperformance their clients did not benefit from it. This is the case because on average investors invest in factor funds after a period of good performance and withdraw after a period of poor performance. In order of factor investing to add value for society, it needs to be a strategic decision. As such, long-term investment horizon is required just like investing in any other strategic asset class – equities, fixed income or alternatives. All of them can have negative returns over short periods and timing skills have been shown to be notoriously difficult. A similar mindset is required when investing in factor premiums. The best thing investors can do is to diversify across factor premiums and have a long-term investment horizon.

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Summary

This section briefly summarizes the main studies and conclusions of this dissertation. In chapter 1 we provide an overview of the most important contributors to the growth of factor investing. In chapter 2 we analyze the price impact during factor index rebalancing. Chapter 3 provides a structural way to define the quality factor and chapter 4 investigates the allocation behavior of investors in factor investing mutual funds.

Chapter 1 puts factor investing in the context of global trends in empirical asset pricing and investment management as an industry. We study the growth of factor investing in the mutual funds industry and attribute it to academic studies which initially triggered it. Despite the exponential growth over the past ten years factor investing appears to be in its infancy. When compared to the growth of passive investing it becomes evident that the potential for future growth in the popularity of factor strategies is significant.

Chapter 2 provides novel evidence to the fundamental stream of literature on market efficiency. It shows that underlying fundamental information is not the only determinant of asset prices. Namely, index tracking can permanently move stock prices away from their previous equilibrium. As such, it has a number of practical implications. Public factor indices can become overcrowded. This has an adverse effect on the expected returns of stocks in those indices and consequently on the investors in public factor indices. It also introduces a new principal-agent problem as index trackers can significantly influence the return of their own benchmark by their trading behavior during index rebalancing. This demands the attention of regulators and asset owners to ensure no conflict of interest arises.

Chapter 3 focuses on the definition of a specific factor. Quality is the newest documented factor in asset pricing and debates on how exactly it should be defined are thriving both in academia and the investment industry. Instead of focusing on a definition which generates the highest abnormal returns we identify the underlying driver of abnormal returns. In this way, we propose a structural way to definite quality. Specifically, we find that quality measures can predict future stock returns if and only if they are good proxies for future earnings growth. As such a good quality definition is one which has strong predictive power for future earnings growth.

Chapter 4 investigates the most important question when it comes to benefits for society as a whole. Namely, do investors benefit from all empirical asset pricing evidence. We find that even though factor funds have generated returns in excess of the ones of traditionally managed active funds, investors in factor funds have failed to do so. Despite identifying the right funds, investors show poor timing skills and allocate to them at the wrong moments. Our results show that to increase their probability of success in the long-term investors should strategically allocate to multiple factor premiums and hold on the investment decision.

Nederlandse Samenvatting (Summary in Dutch)

Dit hoofdstuk vat de belangrijkste resultaten van de studies in dit proefschrift kort samen. In hoofdstuk 1 geven we een overzicht van de belangrijkste aspecten die hebben bijgedragen aan de groei van Factor Investing. In hoofdstuk 2 analyseren we of een prijsimpact kan worden waargenomen tijdens het herbalanceren van de zogenoemde Factor Investing indices. In hoofdstuk 3 onderzoeken we de voorspellende waarde van verschillende Quality factor definities voor aandelenrendementen. Tenslotte onderzoeken we in hoofdstuk 4 hoe beleggers alloceren naar Factor Investing fondsen.

Hoofdstuk 1 beschrijft hoe Factor Investing zich heeft ontwikkeld over de tijd in de context van verschillende bevindingen die gedocumenteerd zijn in de academische literatuur. Ondanks de exponentiële groei van Factor Investing over het afgelopen decennium lijkt deze manier van beleggen nog in de kinderschoenen te staan. Door de ontwikkeling van Factor Investing te vergelijken met die van passief beleggen, wordt duidelijk dat er een enorm potentieel is voor verdere groei van deze beleggingsstijl in de toekomst.

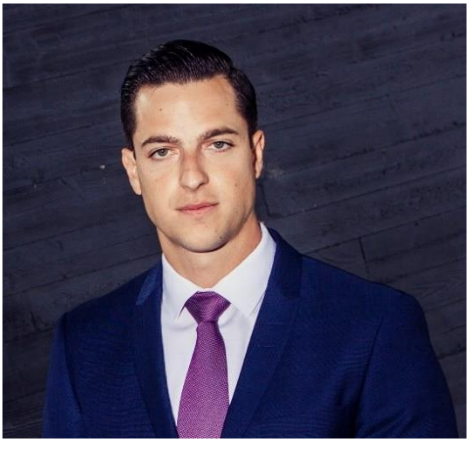
Hoofdstuk 2 biedt nieuwe inzichten in het functioneren van een efficiënte financiële market. In dit hoofdstuk laten we zien dat fundamentele informatie niet de enige determinant is van aandelenprijzen. Het herbalanceren van populaire Factor Investing indices blijkt een permanente prijsreactie te hebben op aandelenprijzen. Dit effect heeft een aantal praktische implicaties. Zo kunnen populaire Factor Investing indices overcrowded raken en zal het verwachte rendement naar beneden bijgesteld moeten worden. Ook lijkt er sprake te zijn van een agent-principaal probleem, omdat indextrackers hun rendementen ten opzichte van de Factor Investing indices kunnen beïnvloeden.

Dit laatste verdient de aandacht van de toezichthouder om er voor te zorgen dat er geen belangenconflict ontstaat tussen beleggers en vermogensbeheerders.

Hoofdstuk 3 richt zich op de verschillende definities die gebruikt worden voor de Quality factor. Deze factor is relatief recentelijk gedocumenteerd en er is nog geen consensus over hoe deze factor moet worden gedefinieerd. In plaats van te concentreren op de kwestie welke definitie de sterkste voorspellende waarde heeft voor toekomstige aandelenrendementen, richten wij ons op het identificeren van de onderliggende oorzaak van deze waarneming. We bevinden dat de Quality definities een voorspellende waarde hebben voor toekomstige aandelenrendementen als en alleen als deze definities ook een goede voorspeller zijn voor de toekomstige winstgroei van de onderliggende bedrijven.

Tenslotte onderzoeken we in hoofdstuk 4 of beleggers in werkelijkheid kunnen profiteren van Factor Investing resultaten die gedocumenteerd zijn in de academische literatuur. We vinden dat, hoewel fondsen die Factor Investing beleggingsstijlen implementeren gemiddeld genomen hogere rendementen behalen dan traditionele actief beheerde fondsen, beleggers in deze fondsen het niet beter doen dan andere beleggers. Ondanks dat beleggers in Factor Investing fondsen in staat zijn de juiste fondsen te identificeren, blijkt dat zij slecht zijn in het timen van het juiste instapmoment. Onze resultaten laten zien dat de kans op succes van beleggers aanzienlijk toeneemt als zij het juiste instapmoment niet proberen te timen, maar als zij een lange beleggingshorizon aanhouden en hun beleggingen over meerdere factoren spreiden.

About the author



Georgi Kyosev was born in Plovdiv, Bulgaria on March 29, 1988. He studied at the High school of Mathematics where he obtained his gymnasium diploma in 2007. From 2007 to 2012 Georgi studied at University of National and World Economy, Sofia Bulgaria, where he received his BSc degree in Finance. He continued his higher education in the Rotterdam School of Management (RSM), Erasmus University in the Netherlands where in 2013 he obtained a MSc degree in Finance and Investments with appellation *cum laude* as well as "best thesis" award. In September 2014 Georgi joined the Department of Finance of RSM Erasmus University as a PhD Candidate. His PhD trajectory was supported by the Erasmus Research Institute of Management (ERIM). He presented his research at several international conferences and seminars, including the 2017 Midwest Finance Association conference in Chicago, the 2018 American Finance Association conference in Philadelphia, and the 2019 Eastern Finance Association conference in Miami. His research has also been featured in leading practitioners outlets such as Bloomberg and Citywire. The article version of chapter "Factor Investing From Concept To Implementation" of his dissertation is published in the *Journal of Portfolio Management*, and the article version of the Chapter "Does Earnings Growth Drive the Quality Premium?" is at a second round of revision at the *Journal of Banking and*

Finance. During his PhD trajectory, Georgi also studied at London School of Economics and Political Science. Georgi's teaching experience includes Master courses in the MSc of "Finance and Investments" and MSs of "Finance and Investments – Advanced" programs as well as supervision of Master theses at RSM Erasmus University. Georgi also teaches executive courses in the field of asset pricing as well as gives lectures for VBA Netherlands. Since 2013 Georgi holds a research position at Robeco Asset Management. His work has been fundamental to the Robeco QI Quality fund, Robeco multi-factor equities, and Robeco multi-factor indices. His research interests include empirical asset pricing and mutual funds.

Portfolio

Ph.D. courses

Course	Institution	Grade	ECTS
Statistical Methods	ERIM	9.2	6
Applied Econometrics	ERIM	8.2	5
Seminar Asset Pricing 1	ERIM	8.5	5
Seminar Asset Pricing 2	ERIM	8.5	5
Programming	ERIM	9.5	4
English	ERIM	CPE certificate	4
Interaction Performance Training / Coaching	ERIM	pass	2
Scientific Integrity	ERIM	pass	1
Publishing Strategy	ERIM	pass	1
Financial Markets	LSE, London UK	A+	8

Teaching

- **Quant and Factor Investing (2016 – 2018):** lectures and workshops. This course is part of the MSc in Finance and Investments Advanced at Rotterdam School of Management, Erasmus University

- **Investments (2017 – 2018):** workshops. This course is part of the MSc in Finance and Investments at Rotterdam School of Management, Erasmus University

- **Research skills (2016 – 2018): l**ectures. This course is part of the MSc in Finance and Investments Advanced at Rotterdam School of Management, Erasmus University

- **Financial Modelling (2019):** lectures. This course is part of the MSc in Finance and Investments at Rotterdam School of Management, Erasmus University

- **Executive courses (2017 – 2018): l**ectures on empirical asset pricing and mutual fund performance for VBA Netherlands and private investment companies.

- **Master thesis (2014 – 2016):** supervising students in writing their thesis to graduate from the MSc in Finance and Investments at Rotterdam School of Management, Erasmus University

    - On the link between information asymmetries and mutual fund performance: A study of sector funds, *(Moritz Schmidt)*

    - Information, Dispersion, and Idiosyncratic Volatility, *(Yaoyue Zhang)*

    - Generalist or specialist; How important is my network? Venture capital investment concentration and network breadth as drivers of syndication *(Jelle Nagelhoud)*

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- The Impact of Credit Rating Changes on Leverage levels - Differences between banking and non-banking industries, *(Ellen Mertens)*

- The effect of a corporate credit rating change on subsequent firm performance: A stakeholders approach, *(Bas Ribbers)*

Conferences

- **MFA 2017:** Midwest Finance Association, 66th Annual Meeting, Chicago Illinois**.**

- **AFA 2018:** American Finance Association Annual Meeting, Philadelphia, Pennsylvania.

- **EFA 2019:** Eastern Finance Association, 55th Annual Meeting, Miami, Florida.

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Georgi Kyosev was born in Bulgaria on March 29, 1988. After graduating from High School of Mathematics, he continued his education in the field of Finance. In 2013 he obtained a MSc degree in Finance and Investments with appellation *cum laude* as well as "best thesis" award at Erasmus University in the Netherlands. In September 2014 Georgi joined the Department of Finance of RSM Erasmus University as a PhD Candidate. He presented his research at several international conferences, and one of his studies is published in the *Journal of Portfolio Management*. Since 2013 Georgi holds a research position at Robeco Asset Management where he focuses on developing and implementing factor investing strategies.

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