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Momentum in smart beta exchange-traded funds

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ABSTRACT:
Momentum is one of the most puzzling pricing anomalies discussed in the academic literature as past returns should not predict future returns under the efficient market theory. Asset pricing models have failed to explain momentum returns across different markets and asset classes while academics have argued about the reasons behind the success of momentum strategies. Momentum is stronger among industries and many papers have studied industry momentum in exchange-traded funds. More recent evidence suggests that industry and individual stock momentums originate from factor momentum. This thesis aims to extend factor momentum into the universe of exchange-traded funds by implementing relative-strength and time-series momentum strategies in 24 smart beta exchange-traded funds traded on the U.S. over the sample period of August 2000 to February 2020. Implementation of momentum strategies generates substantially large transaction costs due to the high trading volume required by the strategies. Smart beta exchange-traded funds offer investors easier access to factor momentum strategies with lower transaction costs. Thus, the purpose of this thesis is to examine whether individual investors can gain similar abnormal factor momentum returns documented in earlier studies by exploiting momentum strategies in smart beta exchange-traded funds. This thesis contributes to the earlier momentum studies in exchange-traded funds with a longer sample period that provides further evidence over the post-crisis period of the recent financial crisis. Three regressions of the Fama-French three, five, and six-factor models are used to test the profitability of the momentum strategies. Contrary to the results of factor momentum documented in earlier studies, the results from the regression models show that all abnormal returns are either negative or statistically insignificant. Furthermore, the results show that exchange-traded fund momentum strategies remain unprofitable with a longer post-crisis sample period. The thesis concludes that momentum strategies in smart beta exchange-traded funds are unprofitable and investors are not able to achieve abnormal returns by exploiting these strategies. The differing results with the earlier factor momentum studies might emerge from the simplistic factor approach used by the smart beta exchange-traded funds that could lead to unintended factor exposures. The exchange-traded fund market might also be more efficient than the stock markets. Another explanation for the failure of momentum in exchange-traded funds could be the small spreads between the past winners and losers. Future research could try to explain the reasons behind the reported momentum discrepancies between exchange-traded funds and individual stocks.

KEYWORDS: exchange-traded fund, momentum, anomalies, profitability, strategies

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1 Introduction

The purpose of this thesis is to examine the profitability of momentum strategies in smart beta exchange-traded funds. The Momentum effect is a well-recognized phenomenon in stock markets and one of the most puzzling asset pricing anomalies discussed in academic literature. The momentum effect initially documented by Jegadeesh & Titman (1993) seems to violate the weakest form of the efficient market theory as most of the asset pricing models fail to explain momentum returns (Fama-French 1996; 2015; 2017). Historical prices should not predict future prices if new information is reflected immediately in asset prices unless changes in systematic risk correlate with prior returns (Ehsani & Linnainmaa 2019). In contrast with the efficient market theory, Jehadeesh & Titman (1993) show that past one year returns predict future returns by reporting significant positive returns with momentum strategies that buy stocks with high prior returns and sell stocks with low prior returns.

Asness, Moskowitz, & Pedersen (2013) show that momentum is prevailing and strong across different markets and asset classes. Furthermore, Hou, Xue & Zhang (2018) show that momentum is one of the few anomaly groups studied in the academic literature that are statistically robust for replication emphasizing the strong existence of momentum effect. Moskowitz & Grinblatt (1999) show that past returns of industries predict future returns of the industries. The result documented by Moskowitz & Grinblatt (1999) shows that industry momentum provides significantly higher profits than individual stock momentum. However, some argue that momentum profits are illusionary as the implementation of momentum strategies generates substantially large transaction costs due to the high trading volume required by these strategies (Lesmond et al. 2004). Exchange-traded funds offer investors an opportunity to implement momentum strategies with lower trading volume and transaction costs.

Inspired by the findings of Moskowitz & Grinblatt (1999) many papers have been published in the academic literature that extends industry momentum into the field of exchange-traded funds that provide investors easy access to sector allocation. Andreu, Swinkels & Tjong-A-Tjoe (2013) report a 5% annual excess return for momentum strategies in the country and sector ETFs. However, the results are not strong from a statistical point of view as the results are statistically not different from zero. Du, Denning & Zhao (2014) study sector ETF momentum in the post-2000 period and find that sector ETFs don’t exhibit momentum. Furthermore, Tse (2015) finds no significant momentum returns in sector ETFs with relative-strength strategies, and positive returns observed from the time-series strategies are mainly achieved during the financial crisis period of 2007-2009.

However, more recent studies conducted by Arnott, Clements, Kalesnik & Linnainmaa (2019), and Ehsani & Linnainmaa (2019) suggests that industry and stock momentums stem from factor momentum. Factor momentum is stronger than industry momentum as Arnott et al. (2019) show that momentum strategies that invest in factors based on their prior returns are more profitable than industry momentum strategies. Thus, this thesis aims to extend factor momentum into the universe of ETFs by implementing momentum strategies in smart beta ETFs that track specific factors.

Smart beta ETFs offer clear advantages and opportunities for individual investors who seek to implement momentum strategies. For instance, smart beta ETFs offer greater accessibility and asset allocation to different factor exposures. In addition, investors are able to reduce transaction costs of momentum strategies as ETF momentum requires less trading than traditional stock momentum. ETF trading produces smaller transaction costs than trading individual stocks because ETFs have smaller bid-ask-spreads and are more liquid which reduces the price impact of large trades (De Jong & Rhee 2008). It is interesting to examine whether different results can be observed with factor momentum strategies in ETFs than previously reported from sector ETFs. The data sample used in this thesis considers more ETFs and has a longer sample period than earlier studies reported on ETF momentum. The longer sample period of this study will provide a closer insight into ETF momentum during the post-crisis period.

1.1 Research question and hypothesis

The purpose of this thesis is to examine the profitability of momentum strategies in smart beta exchange-traded funds. This thesis extends factor momentum to the universe of exchange-traded funds and expands previous studies of ETF momentum into smart beta ETFs. This thesis attempts to find out whether smart beta ETFs exhibit momentum effect similar to factor momentum in common stocks that would allow investors to gain abnormal returns by implementing momentum strategies in smart beta ETFs. Thus, the null hypothesis and alternative hypothesis applied in this thesis are as follows:

H_0: Smart beta ETF momentum strategies are not able to provide statistically significant and positive abnormal returns

H_1: Smart beta ETF momentum strategies can provide statistically significant and positive abnormal returns

The hypotheses are limited to consider only positive abnormal returns as the purpose of this thesis is indeed the profitability of momentum strategies. The aim is to reject the null hypothesis and prove that momentum strategies in smart beta ETFs are significantly profitable at the 5% significance level. Inspired by Tse (2015), Arnott et al. (2019), and Ehsani & Linnainmaa (2019) the profitability of smart beta ETF momentum is examined through both relative-strength and time-series momentum strategies. In total eight strategies with different ranking and holding periods are formed for both relative-strength and time-series. The hypotheses described above apply for all momentum strategies considered in this thesis. In other words, all of the strategies are separately tested for the hypothesis. In order to test the hypothesis, the alphas of the smart beta ETF momentum strategies are computed from three regressions of the Fama-French three, five, and six-factor models. Thus, to reject the null hypothesis, positive alphas at the 5% significance level should be observed from all of the three different factor model regressions.

1.2 Structure of the thesis

The thesis is structured as follows. This first chapter provides an introduction to the thesis by introducing the theoretical background, earlier studies, and outlining the purpose and research hypothesis for the thesis. The next three chapters two, three, and four will build up the theoretical framework of the thesis. Chapter two will briefly explain the structure and mechanics of ETFs. The latter part of chapter two will describe the structure of smart beta ETFs and provide the theoretical background for the factors that smart beta products try to capture. Chapter three considers the basic principles of efficient market theory and discusses how market efficiency is determined into the three forms of efficiency. Later in chapter three, the four common asset pricing models are introduced including the Fama-French three, five, and six-factor models that are used as regressions in this thesis. Chapter four defines the concept of momentum effect and explains how momentum strategies are formed. Rational and behavioral explanations for momentum effects existence are discussed in the latter part of chapter four. Chapter four also provides a more detailed discussion about previous studies of ETF momentum.

Chapter five introduces the sample and data used in this thesis as well as describes the methodology utilized for testing the hypothesis presented in chapter 1.1. Moreover, chapter 5.2 describes the procedure applied in this thesis to form momentum portfolios and introduces the regressions used in the thesis. Later the results that have been obtained through the introduced data and methodology are provided in chapter six. The empirical results are divided into two sections in chapter six. First, the results from relative-strength strategies are discussed. The descriptive statistics for all eight momentum strategies implemented in the study are presented as well as the empirical results from the three regressions models. Later, the results from time-series momentum strategies are presented and discussed in the same manner. Furthermore, in chapter six, the results are compared against previous results documented in the academic literature. Chapter seven will conclude the findings and results provided by the thesis.

2 Exchange-traded funds

An exchange-traded fund (ETF) is a financial product that aims to follow the performance of a specific index. ETFs are constructed from a pool of securities like stocks and bonds and they try to mimic their benchmark index. ETFs are a new version of traditional mutual funds but have several major differences. For example, ETF shares can be bought and sold short throughout the day like stocks opposite to traditional mutual funds. (Lettau & Madhavan 2018.)

The first ETF called SPDR (Standards & Poor's Depository Receipt) was introduced in 1993 and it aims to follow the performance of the S&P 500 index. In later years in addition to traditional ETFs following broad market indexes, other types of ETFs were introduced. Especially, industry-sector, commodity, bond, and international ETFs have grown rapidly since the late 1990s. In recent years ETFs that are constructed to follow specific investment strategies used by active mutual funds and hedge funds have rear its head. For example, iShares MSCI USA Momentum Factor (MTUM) ETF is this kind of an ETF that is formed to capture momentum. (Bodie et al. 2014:104; Lettau & Madhavan 2018.)

ETF markets have grown rapidly since the launch of the SPDR in 1993 and ETFs have been even described as "one of the most important financial innovations in decades" by Leattau & Madhavan (2018). In 2008 there were 1600 ETF's traded globally whereas at the end of March 2020 the number of ETFs for investors to choose from is over 7000 (ETFGI 2020). Global ETF assets have grown from 0.7 trillion (USD) to over 5 trillion (USD) over the past ten years (ETFGI 2020). According to BlackRock (2020) estimates the growing trend is possibly to be continued as they predict that global ETF assets will exceed 12 trillion (US$) by the end of 2023.

Buying an ETF share one receives a claim on a fund that holds a pool of securities. ETF shares are created in the so-called "primary market" where an authorized financial institution issues a pool of securities to ETF manager and in return receives ETF shares. An authorized financial institution can sell these ETF shares in the "secondary market" to investors through brokerage firms. Investors can buy on margin and sell short ETF shares throughout the day like common stocks. ETF's share price can differ from its net asset value (NAV) opposite to traditional mutual funds which can be traded only at their end of the day NAV. However, the difference between ETFs share price and NAV is controlled by the power of creating and redeeming ETF shares used by the authorized financial institution. (Poterba & Shoven 2002.)

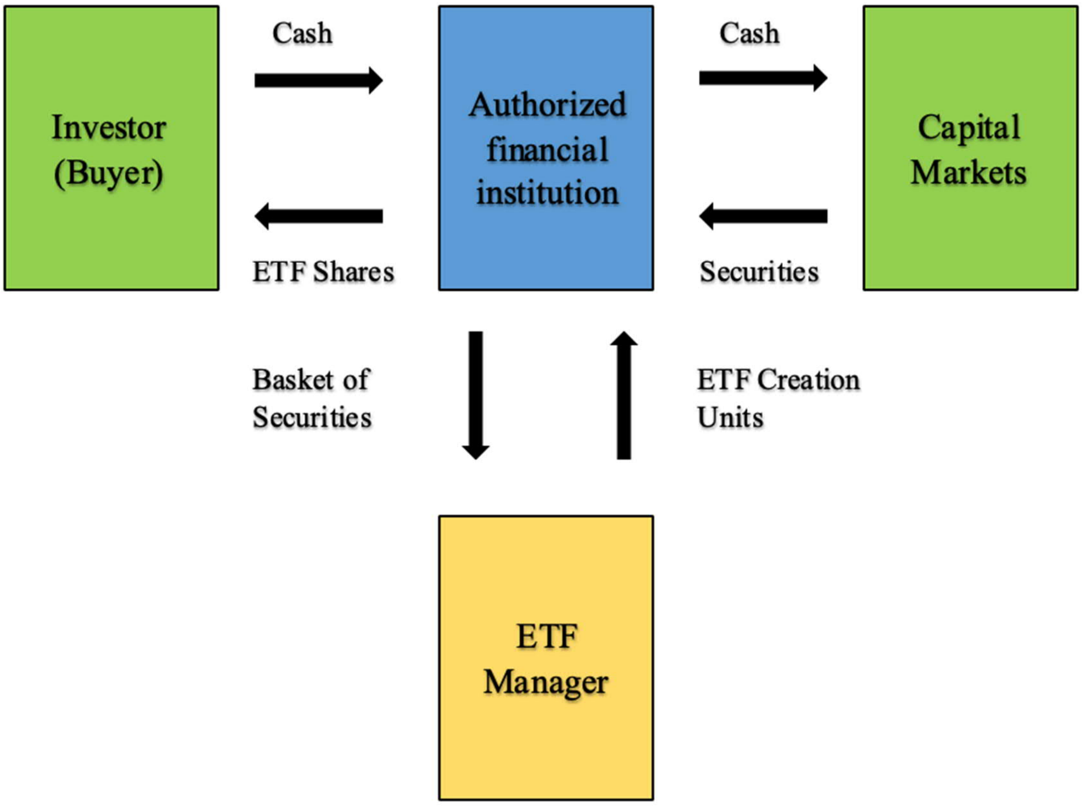

Figure 1. Structure and mechanics of ETFs (Lettau & Madhavan 2018).

The creation/redemption mechanism is shown in figure 1 where the authorized financial institution adjusts ETF shares in response to supply and demand by creating or redeeming shares with ETF manager. If the ETF share price is too high compared to its NAV, the authorized financial institution can create new ETF shares by buying a basket of securities matching or very similar to ETFs holdings. Then the financial institution can deliver the basket of securities to the ETF manager in exchange for ETF shares known as creation units. If the ETF share price is too low compared to its NAV, the authorized financial institution can redeem ETF shares by buying those shares and exchange them to a basket of securities with the ETF manager. Thus, the authorized financial institutions together with ETF managers can increase or decrease the number of outstanding ETF shares in the market. (Lettau & Madhavan 2018; Poterba & Shoven 2002.)

ETFs offer lower transaction costs and tax-advantages to investors than traditional mutual funds. Even though investors have to acquire ETF shares through brokers with a fee, it may lower total management fees as the fund saves costs on distribution, record-keeping, and on marketing fees to small investors. More importantly, as ETFs are not traded directly with the fund it provides lower transaction costs because the secondary market trading does not affect the underlying securities. Thus, transaction costs that are formed when investors are redeeming their shares are reduced significantly. (Bodie et. al 2014:106; Lettau & Madhavan 2018.)

ETFs ability to significantly reduce or even eliminate transaction costs and gain tax-advantages over traditional mutual funds is based on the creation/ redemption mechanics of ETFs. Large redemption of mutual fund shares can create capital gains taxes for the remaining shareholders to be paid as the mutual fund is forced to sell the underlying securities to meet the redemption. In large ETF share redemptions, the ETF managers have the option to meet the redemption by delivering the underlying securities to the redeeming party instead of cash. Hence, ETF managers have the opportunity to eliminate possible capital gain taxes to ETF investors by avoiding the selling of the underlying securities. (Poterba & Shoven 2002; Bodie et al. 2014:106.)

The rapid and large growth in the popularity of exchange-traded funds can be explained by the many benefits these financial products have to offer. ETFs are a good option for investors who trade with high volume and seek short-term liquidity because of the possibility to trade ETF shares throughout the day (Poterba & Shoven 2002). Defining funds investment strategies beforehand and listing funds holdings every day provides larger transparency on ETFs over traditional mutual funds which list their holdings only quarterly (Lettau & Madhavan 2018). Investors can easily diversify their investment portfolios across different asset classes through ETFs. In the context of this thesis, the opportunity to sell short and buy ETF shares on margin provides an interesting benefit for investors. As individual investors may not be able to utilize momentum strategies due to trading constraints and higher transaction costs, exchange-traded funds give investors a fast access to capitalize on market momentums (Tse 2015).

2.1 Smart-beta

Smart beta or factor exchange-traded funds are investment products that follow specific factors through different weighting methods (Jacobs & Levy 2014). Smart beta can be defined broadly as a group of indices and exchange-traded products that track these smart beta indices (Morningstar 2019). Smart beta ETFs try to outperform the market portfolio by exploiting different weighting methods than traditional market indices by focusing on specific factors that are associated with stock returns (Lettau & Madhavan 2018). Smart beta ETFs can be characterized as an investment product that uses both active and passive investment strategies. Similarly to active mutual funds and hedge funds also smart beta ETFs exploit the same exposure to different factors. However, smart beta ETFs are not actively managed by a manager as they follow transparent trading rules that track specific indices. Thus, smart beta ETFs can be identified somewhere between active and passive investing. (Lettau & Madhavan 2018.)

In recent years smart beta ETFs have become increasingly popular as investors are seeking to capture factor premiums (Lettau & Madhavan 2018). First smart beta ETFs the IShares Russell 1000 Growth (IWF) and the IShares Russell 1000 Value (IWD) were introduced in the U.S. market in May 2000. Since then the smart beta universe has grown even more rapidly than the broader ETF market. The rapid growth has been driven by new cash flows and launches as well as by new issuers entering the market. However, the pace of new launches has decreased more recently, which implies that the smart beta ETF market has started to saturate (Morningstar 2019). At the end of February 2020, there were 1,311 smart beta equity ETFs available worldwide with assets of 787 billion (USD) (ETFGI 2020).

Smart beta ETFs aim to increase their returns or adjust their risk exposures by engaging rules that exploit specific factors or sets of factors (Morningstar 2019). Such factors that smart beta products seek to capture are for example value, growth, momentum, size, low volatility, quality, growth, and various others (Jacobs & Levy 2014). For instance, Morningstar (2019) categorizes smart beta ETFs into 11 different strategic-beta groups based on their factor exposure. However, this thesis centers on six common factors: value, size, momentum, low volatility, quality, and growth that are backed by strong theoretical evidence studied in the academic literature and are widely used strategies by hedge funds and active mutual funds.

Academic literature has argued over the years that investment strategies that are based on value characteristics are able to outperform the market (Graham & Dodd 1934; Dreman 1977). The basis of these value strategies is for buying stocks that have low ratios of stock prices to value measures such as earnings, dividends, historical prices, and book assets (Lakonishok, Shleifer & Vishny 1994). Stocks with low price to earnings ratios offer higher returns than stocks with a high price to earnings ratio (Fama & French 1992, Lakoshinok et al. 1994). Thus, value strategies take for example long positions in high book-to-market firms and short positions in low book-to-market stocks as cheap stocks generate higher returns than expensive stocks (Fama & French 1993; Lakonishok et al. 1994).

The size effect initially documented by Banz (1981) is about the relationship between returns and the total market value of common stocks. Banz (1981) finds that on average smaller firms have higher risk-adjusted returns than larger firms that imply that the capital asset pricing model is inadequate for pricing assets. The main idea of size strategies is that smaller stocks tend to generate higher returns than larger stocks in the long-term. Thus, the size factor tilts towards smaller stocks by buying small stocks and selling large stocks. (Banz 1981.)

Momentum is one of the well-known anomalies reported in academic literature. According to the weak form of efficient market theory past price information should not predict future prices as prices should adjust to new information without delay (Malkiel 2003). However, Jegadeesh & Titman (1993) show that past one year returns predict future returns by reporting significant positive returns with momentum strategies that buy stocks with high prior returns and sell stocks with low prior returns. The basic idea of momentum strategies is to buy stocks that have high relative prior returns and sell stocks that have low relative prior returns. Asset pricing models of Fama-French three and five-factor models have struggled to capture momentum profits (Fama & French 1996; 2015; 2017). Thus, encouraged by popular demand Fama & French (2018) add momentum factor to the five-factor model.

Low volatility or betting against beta strategies are also in contrast with the basic finance principles as low-volatility stocks and low-beta stocks have been able to outperform high-volatility and high-beta stocks over a long period (Baker, Bradley & Wurgler 2011). Baker et al. (2011) show that low risk offers consistently higher returns than high risk regardless of whether the risk is defined by beta or volatility. Furthermore, Frazzini & Pedersen (2014) show that high beta is associated with low beta across asset classes and different equity markets as they find significant positive risk-adjusted returns for portfolios that are long leveraged in low-beta assets and short in high-beta assets. Thus, low volatility portfolios yield positive alphas by buying stocks with lower risk and selling stocks with higher risk (Baker et al. 2011; Frazzini & Pedersen 2014).

Asness, Frazzini & Pedersen (2019) suggest that stock prices should increase with their quality characteristics such as profitability, growth, and safety. Profitability can be measured through e.g. gross profits, margins, earnings, accruals, and cash flows. Growth characteristics can be defined by the growth rate of these profitability measures. Safety can be considered through return based methods such as market beta and fundamental based methods such as low volatility of profitability, low leverage, and low credit risk. Hence, stocks can be identified as high-quality stocks or low-quality stocks through a combination of these measures and characteristics. Asness et al. (2019) show that quality portfolios that buy high-quality stocks and sell low-quality stocks can yield significant risk-adjusted returns. Thus, the quality factor is indeed based on buying high and selling low-quality firms sorted for example by firms' return-on-equity and debt-to-equity ratios. (Asness et al. 2019.)

Growth factor tilts towards stocks that tend to have high price-to-earnings, and price-to-sales and low book-to-market ratios (Lettau & Madhavan 2018). As discussed above growth stocks tend to be outperformed by value stocks. However, Mohanram (2005) shows that growing firms outperform firms that have poor growth by forming long-short portfolios based on firms' growth characteristics such as cash flows, earnings stability, growth stability, capital expenditure, advertising, and intensity of research and development. For example, a growth portfolio goes long (short) on stocks with high (low) sales per share and earnings per share growth rates. A long-short portfolio that buys stocks with good growth characteristics and sells stocks with poor growth characteristics is able to earn significant excess returns (Mohanram 2005).

Smart beta ETFs try to capture factors discovered in academic research by tracking specific indices. For instance, considering MSCI factor indexes, the MSCI Value Weighted Indexes capture value factor by weighting variables such as sales, earnings, cash flow, and book value. The low size factor is captured by the MSCI Equal Weighted Indexes that equal weights all stocks in the parent index. The momentum effect is reflected by the MSCI Momentum Indexes that weight stocks based on prior 6 and 12-month volatilities. The MSCI Minimum Volatility Indexes aim to capture low volatility factor by using minimum variance optimization. High-quality stocks are captured by the MSCI Quality Indexes by weighting based on return-on-equity, debt-to-equity, and earnings variability. Whereas exposure to growth factor is captured for example by the MSCI World Growth

Index that is constructed through variables such as long and short-term forward earnings per share growth rates, current internal growth rate, long-term earnings per share growth trend, and long-term historical sales per share growth trend. (Bender, Briand, Melas & Aylur Subramanian 2013; MSCI 2020.)

Smart beta ETFs offer clear advantages and opportunities for factor investing and momentum strategies. Investors had limited options to gain exposure to factors before the launch of the first smart beta ETFs. Investors had to either buy individual stocks directly from a broker or to invest in actively managed mutual funds, which both generate substantial transaction costs and management fees. Whereas smart beta ETFs enable investors easy access to different factor exposures with lower cost. Also, investors can reduce the transaction costs of momentum strategies as ETF momentum requires less trading than traditional stock momentum. However, smart beta ETFs might fail to efficiently capture the intended factors and lead to unintended exposures due to the simplistic factor approach of smart beta ETFs (Jacobs & Levy 2014). For example, using simple value measures could lead to exposure to distressed firms instead of gaining factor exposure to high-value firms. Furthermore, smart beta ETFs are long-only unlike the factors discussed in the academic literature that might decrease the intended factor exposure. (Lettau & Madhavan 2018.)

3 Efficient Markets

This section introduces the basic principles of efficient market theory. The efficient market theory presented by Fama (1970) and its three forms of weak, semi-strong, and strong forms are discussed. The later part of this section is focused on tests for market efficiencies and asset pricing models.

3.1 Efficient market theory

An efficient market is defined by Fama (1970) as a market where prices always fully reflect all available information. Capital markets' primary task is to distribute spare capital efficiently to productive use. Thus, an efficient market can be seen as a market where accurate signals for resource allocation are offered by prices. An efficient market where prices always fully reflect all available information is a market where companies can make production-investment decisions and investors can base their decisions on the ownership of firms' activities. (Fama 1970.)

In order to prices fully reflect all available information at any time has Fama (1970) introduced three conditions for capital market efficiency. According to Fama (1970) markets are efficient when:

1. "There are no transactions costs in trading securities"
2. "All available information is costless available to all market participants"
3. "All agree on the implications of current information for the current price and distributions of future prices of each security"

Even though under these conditions' prices would always reflect all available information and thus markets would be efficient it cannot be said that these conditions are met in the real world. However, this doesn't mean that the markets are inefficient. High transaction costs don't necessarily imply market inefficiency as long as investors take notice of all available information. Even if all available information is not available to everyone without any costs markets can be still efficient if an adequate number of market participants have quick and easy access to the available information. Investors' different views about the implications of available information do not necessarily make markets inefficient if investors are not able to make continuously better valuations of available information than the market prices imply. (Fama 1970.)

The basic idea of the efficient market hypothesis is that abnormal returns are unachievable because the prices fully reflect all the available information at any time. The efficient market hypothesis lays on the assumption that new information spreads quickly across market participants and that the stock prices adjust to this new information without delay. Hence, investors who exploit fundamental analysis or technical analysis to construct different investment strategies are not able to achieve higher returns than a randomly selected portfolio of individual stocks without bearing greater risk. In other words, if markets are efficient it's impossible to achieve greater returns than average without accepting greater risk than average. (Malkiel 2003.)

3.2 Three forms of efficiency

Market efficiency can be categorized into three forms. The difference between these forms is how they determine all available information (Bodie, Kane & Marcus 2014: 353). These forms of efficiency are weak, semi-strong, and strong form. The efficient market hypothesis is an extreme null hypothesis which cannot be expected to be plainly true. By using these categories, it is possible to define the information level when the null hypothesis breaks down. Weak form tests focus only on the historical information about past prices and/or returns whereas semi-strong form tests how quickly prices adjust to other public information such as stock splits, annual reports, and new security issues announcements for example. Strong form tests the existence of any unpublished insider information which can be used to predict the formation of prices by only a subset of market participants. (Fama 1970.)

The weak form hypothesis considers all available information as information that can be distinguished by investigating past stock prices, trading volume, or short interests. According to the weak form hypothesis, the market's stock prices reflect all this information and therefore it would be useless to follow the trends of past stock prices. The hypothesis assumes that all market participants have access to information without any costs. Under this assumption, the investors are able to exploit the positive signals of past stock prices which will eventually make these signals insignificant since the signals are widely known among all market participants. For example, a positive signal of stocks future price would make the price increase instantly to its fundamental level. Thus, the investors cannot predict future prices from historical prices and the market can be claimed to be efficient under the assumptions of the weak form hypothesis. (Bodie et al. 2014: 353.)

A market that meets the terms of the semi-strong form hypothesis is a market where all available public information of the firms' prospects is reflected in stock prices. Public information about firms' prospects include fundamental such as the firm's product line, the expertise of management, patents held, earning forecasts, annual reports, accounting practices, and new security issues as well as stock split announcements. The market meets the terms of semi-strong form hypothesis if all of this public information is available for all investors and they all agree on the implications of this information. (Bodie et al. 2014: 353; Fama 1970.)

Strong form hypothesis assumes that prices fully reflect all available information including private company information. Fama (1970) has stated that the strong form hypothesis should be viewed as a benchmark for future researches about market efficiency due to the extremeness of the hypothesis. Exploiting insider information to gain trading profits is contrary to law and it's highly monitored by authorities. However, the definition of what is insider information and what is not can be wavering. The strong form of efficiency is still a good approximation of reality. (Bodie et al. 2014: 354; Fama, 1970.)

It cannot be expected that all available information would be reflected in prices at any given time. Investors are continuously seeking new information and opportunities to gain extra profits. Afterward, conclusions can be made showing that the market prices have been significantly above or below its fundamental level. It is remarkable to remember that the efficient market theory is based on assumptions that form an extreme null hypothesis that cannot be anticipated to be plainly true. However, it is possible to define the market efficiency level by exploiting the three forms of efficiency. As the efficient market theory considers given time and current information it is uncertain if today's prices are truly at their fundamental level. Even though prices can be expected to be at their fundamentals on average if we assume that the markets function rationally. (Bodie et al. 2014: 354; Fama 1970.)

3.3 Tests for market efficiency

In 1991 Fama made modifications on how the three forms of efficiency should be measured. Regarding the weak form hypothesis, he expanded the view of only considering past returns forecasting power to a wider and more general perspective of tests for return predictability. For the semi-strong and strong form hypotheses, he preserved the coverage but proposed a change in measuring methods. Fama (1991) proposed event studies to test the semi-strong form hypothesis and tests for private information to challenge the strong form hypothesis. (Fama 1991.)

Instead of focusing only on past returns capability to make predictions about the future Fama (1991) included predictability of dividend yields and interest rates in order to test the level of market efficiency. Instead of considering only the predictability of daily, weekly, and monthly returns, now the tests for the weak form hypothesis also considered long-term predictability of returns. According to Fama (1991) event studies produce the most reliable evidence on market efficiency. As the date of an information event is precise and it has a significant effect on prices it can provide strong implications on how rapidly prices adjust for new public information. For the strong form hypothesis, the long term abnormal returns have to be measured in order to test if investors hold private information that is not been transferred to prices. (Fama 1991.)

The efficient market hypothesis has never been widely approved among market professionals or even academics and the debate will never probably settle down (Bodie et al. 2014: 353). According to Fama (1991), academics tend to disagree about the implications of efficiency even though they agree with the facts that transpire from the tests of market efficiency. This unclarity emerges from the fact that the efficient market is not testable solely due to the joint-hypothesis problem (Fama 1991).

The joint-hypothesis problem is that market efficiency tests must be performed jointly with asset-pricing models. This is problematic when answering the question: "Are prices reflecting information properly?", because the meaning of "properly" is defined by asset-pricing models (Fama 1970). Therefore, the deviation of evidence as a result of the join-hypothesis problem creates indistinctness whether the result is due to market inefficiency or a bad asset pricing model. Thus, precise conclusions about the level of market efficiency are impossible to state without unclarity. (Fama 1970; 1991.)

3.4 Asset pricing models

Asset Pricing Models explain how asset prices are formed and try to determine the measure of risk for a single asset and the market price for risk (Copeland, Weston & Shastri, 2014: 145). This section will introduce briefly the common asset pricing models such as the capital asset pricing model (CAPM), Fama-French three-factor model (FF3), Fama-French five-factor model (FF5), and Fama-French six-factor model (FF6).

The Capital Asset Pricing Model (CAPM) explains how the expected return of an investment should be affected by its risk. CAPM was introduced by William Sharpe (1964), Jack Treynor (1962), John Lintner (1965a; 1965b), and Jan Mossin (1966). The basic idea of the model is that asset prices are not affected by all risk. Especially, a risk which can be faded away by diversified portfolios. The model provides an understanding of the relationship between risk and return and what kind of risk is affecting these returns. (Perold 2004.)

As the model provides understanding about the relationship between risk and returns two important insights can be observed. For estimating different investment options, the relationship provides a benchmark for the rate of return. Thus, it is possible to compare the asset's expected return forecasts to the risk that is related to the asset. Also, it assists in valuations of expected returns on assets that are not yet tradable. (Bodie et al. 2014: 291.)

The capital asset pricing model is formed as it follows:

(1) $$\mathrm{E}_S = r_f + \beta(\mathrm{E}_M - r_f)$$

E_S = expected return on the asset
E_M = expected return on the market portfolio
β = systematic risk of the asset
r_f = risk-free rate
(Perold 2004.)

The CAPM includes four assumptions that simplify the world in order to obtain the model's basic form (Perold 2004). These four assumptions are presented as follows:

1. Investors are avoiding risk and they estimate their portfolios only through expected return and standard deviation of return over the same single holding period.
2. All assets are infinitely divisible, markets are free of transaction costs, short-selling restrictions, and taxes. Information is available to all market participants without any costs and lending at the risk-free rate is available to everyone.

3. All investment opportunities are available to all market participants.
4. Individual asset expected returns, standard deviations of return, and the correlation between asset returns are valued in the same way among all market participants.

   (Perold 2004.)

Even though CAPM is a simple and ideal description of the world it provides deep implications and insights about asset pricing and investor behavior. It provides a platform to examine whether the predictions of the model are met in the real world in investor portfolios and asset prices. Most importantly by using CAPM as a benchmark, it aids understanding market anomalies where asset prices and investor behavior have diverged from the model's prescriptions. (Perold 2004.)

As discussed earlier researchers have shown that stocks average returns can be predictable through firm characteristics like short-term past returns, long-term past return, past sales growth, book to market equity, cash flow/price, earnings/price, and size. Jegadeesh & Titman (1993) proved the continuous of short-term returns called momentum effect where short-term past returns predict future returns and De Bondt & Thaler (1985) showed the reversal of long-term returns called contrarian effect where long-term past returns predict future returns for example. These patterns in average returns are called anomalies which cannot be explained by the CAPM. In order to explain these anomalies, Fama & French (1993) created the Fama French three-factor model. (De Bondt & Thaler 1985; Fama & French 1996; Jegadeesh & Titman 1993.)

In 1992 Fama & French suggested that if stock prices are formed rationally the disparity of average return are a result of differences in risk and therefore stock risks have multiple dimensions. They found that size and book-to-market equity proxies the sensitivity of common risk factors in returns. Later in 1993 Fama & French introduced the three-factor model to explain stocks' average returns. The model is constructed by the market factor, size factor, and book-to-market also known as the value factor. (Fama & French 1992; 1993; 1995.)

The three-factor model states that portfolios expected return that exceeds the risk-free rate $[E(R_i) - R_f]$ can be explained by the sensitivity of its return to the market, size, and book-to-market factors. The market factor is the exceeded return on a market portfolio $(R_M - R_f)$, the size factor is the difference between small stocks return and the large stocks return (SMB, small minus big) and book-to-market factor is the difference between high book-to-market stocks return and the low book-to-market stocks return (HML, high minus low). (Fama & French 1996.)

The Fama-French three-factor model equation is formed as it follows:

(2) $$R_i - R_f = \alpha_i + b_i\left(R_M - R_f\right) + s_i SMB + h_i HML + \varepsilon_i$$

Where R_i is the return on security or portfolio i, R_f is the risk-free return, R_M is the return on the market portfolio, α_i is the intercept, ε_i is the zero-mean residual and b_i, s_i and h_i are the sensitivities of security i to each factor. If the factor sensitivities capture all variation in expected returns when the parameters are seen as real value, the intercept for all securities and portfolios i is zero. (Fama & French 2015.)

Fama & French three-factor model explains most of the anomalies that are based on average returns, which the CAPM is unable to explain. For example, abnormal returns of the contrarian effect proved by De Bondt & Thaler (1985) can be explained through the three-factor model. Fama & French (1996) showed that stocks with high (low) long-term returns in the past have negative (positive) SMB and HML slopes and have lower (higher) future average returns. Interestingly, Fama & French (1996) were not able to explain Jegadeesh's & Titman's (1993) momentum effect due to the findings showing that stocks with high (low) short-term past returns tend to have negative (positive) sensitivity on

HML which indicates more reversal than a continuation of future returns. (Fama & French 1996.)

Researchers have argued that the three-factor model is lacking because it doesn't consider the relation of profitability and investments to average returns. For example, according to Novy-Marx (2013) the expected profitability and according to Aharoni, Grundy, & Zeng (2013) investments are both strongly related to average returns. Inspired from these findings Fama & French (2015) added profitability and investment factors to their model to also capture the variation of average returns related to profitability and investments. (Fama & French 2015.)

The five-factor model equation is presented as it follows:

$$(3) \qquad R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + r_i RMW + c_i CMA + \varepsilon_i$$

Where, RMW (robust minus low) is the difference of returns between stocks with robust profitability and stocks with low profitability, CMA (conservative minus aggressive) is the difference of returns between stocks of high investment firms and stocks of low investment firms, r_i is the sensitivity of stock i to the factor RMW and c_i is the sensitivity of security i to the factor CMA. The intercept α_i for all securities and portfolios i is zero if factor sensitivities are able to capture all of the variations in expected returns. (Fama & French 2015.)

Fama & French (2015; 2017) proved that the five-factor model is better at explaining average return patterns than the three-factor model. However, the five-factor model is unable to explain the average returns of momentum effect and the small stocks low average returns whose returns behave similarly to firms that are aggressive on investing but have low profitability. In 2017 Fama & French also found that investments are negatively related to average returns and therefore the relevance of investment factor is questionable. Interestingly they proposed that future studies should include momentum as an additional factor to the model. (Fama & French 2015; 2017.)

In their more recent paper, Fama & French (2018) suggested augmenting the momentum factor to the five-factor model. Fama & French (2018) try to provide insights about the choice of factors and explanatory power of asset pricing models by using maximum squared Sharpe ratios as a metric for comparing different models. Choosing the right factors for asset pricing models has become increasingly challenging as Harvey, Liu & Zhu (2016) show by identifying 316 anomalies that are potential factors for asset pricing models. Fama & French (2019) consider nested models that are the CAPM, the three-factor model, the five-factor model, and a six-factor model that includes the momentum factor and non-nested models that examine the six-factor model's factor choice through three issues. The first issue regarding the factor choice in the six-factor model is whether to use cash profitability or operating profitability as a profitability factor. The second choice is between long-short spread factors and excess return factors and the third choice is whether to use factors with big or small stocks or factors that use both. (Fama & French 2018.)

Academic literature has argued over a long time about the explanations behind the momentum effect. Academics have tried to explain momentum profits through time-varying risk, behavioral biases, and trading frictions (Ehsani & Linnainmaa 2019). However, at the same time, momentum has been considered as an independent factor due to the strong empirical robustness and existence of momentum over time and across asset classes (Ehsani & Linnainmaa 2019). Models without the momentum factor are unable to explain momentum profits whereas models with momentum tend to only capture momentum and nothing else (Fama French 2016; Ehsani & Linnainmaa 2019). Fama & French (2018) raise their concerns about factors that are empirically robust but lack theoretical motivation as it would result in data dredging that produces an extensive list of factors that poses challenges for reliable interpretation of these factors and their persistence. Thus, Fama & French (2018) add the momentum factor to the five-factor model in their own words reluctantly to satisfy insistent popular demand as the momentum factor lacks theoretical motivation even though it is empirically robust.

Fama-French six-factor model including the momentum factor is presented as follows:

(4) $$R_{it} - F_t = \alpha_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + m_i UMD_t + \varepsilon_{it}$$

Where UMD (up minus down) is the added momentum factor that is the difference of returns between high prior return stocks and low prior return stocks, m_i is the sensitivity of security i to the momentum factor UMD, SMB and HML are the size and value factors from the three-factor model, RMW and CMA are the profitability and investment factors from the five-factor model, α_i is the intercept, R_{it} is the return on an asset in month t, F_t is the risk-free rate, Mkt_t is the excess return of the market portfolio over F_t. (Fama & French 2018.)

Fama & French (2018) use left-hand-side and right-hand-side approaches to compare factor models and factors. The left-hand-side approach compares models based on the intercepts of the model regressions when portfolios excess returns are regressed through the model. In the right-hand-side approach in order to test factors' importance in explaining average returns, each factor is regressed on the model's other factors. A factor is important in explaining average returns if the intercept from the regression is different from zero. Fama & French (2018) show that the right-hand-side approach is beneficial for choosing factors in nested models but is not suitable for non-nested models as the models to be compared have distinct factors. For the nested models CAPM, three, five, and six-factor models Fama & French (2018) show that the six-factor model wins at explaining average returns. They confirm that models with cash profitability are better at capturing average returns than models with operating profitability. Furthermore, Fama & French (2018) show that the best model based on the maximum squared Sharpe ratio metric is the model that combines market and size factors with the small stock spread factors of value, profitability, investment, and momentum. (Fama & French 2018.)

4 Momentum

Momentum is about past returns' ability to predict future returns. Momentum strategies buy stocks with high prior returns and sell stocks with low prior returns. Jegadeesh & Titman (1993) documented that strategies which use this kind of approach can produce significant positive returns over 3 to 12 months holding periods. Strategies that select stocks based on their previous returns lay on the assumption that stock prices either underreact or overreact to information (Jegadeesh & Titman 1993).

Jegadeesh & Titman (1993) formed strategies where they observed stock returns over the past 3, 6, 9, and 12 months. Stocks were selected based on the observations of the past returns and the selected stocks were held on the portfolio for 3, 6, 9, and 12 months. This strategy is called J-month/K-month strategy. In this strategy, the selected stocks are ranked in scaled order based on their past returns in the J months at the start of each month t. Based on these rankings, ten portfolios are formed. The top portfolio is called "losers" and the bottom portfolio is called "winners". After forming the portfolios, the strategy is to buy the winner portfolio and sell the loser portfolio every month t and hold this position for K months. The strategy which observed past returns for 6 months and had a holding period of 6 months earned 12.01% annualized average abnormal return over the sample period. (Jegadeesh & Titman 1993.)

Jegadeesh and Titman (2001) retested their (Jegadeesh & Titman 1993) research to evaluate the explanations for the momentum strategy with newer data. They found that the momentum profits continued over the 1990 to 1998 sample period and that the winners kept on winning and the losers kept on losing as they did in the previous research. They proved that the earlier results in 1993 can't be entirely explained by data snooping bias. Bulkley & Nawosah (2009) extended Jegadeeshs & Titman's (1993) research by examining data from NYSE and AMEX from 1965 to 2005. They also found strong evidence that momentum strategies are profitable in U.S. stock markets. (Jegadeesh & Titman 2001; Bulkley & Nawosah 2009)

Jegaheesh & Titman (2001) proved short-term prior returns predict future returns whereas De Bondt & Thaler (1985) documented the reversal of long-term returns that is also called the contrarian effect. The contrarian effect is based on the idea that past losers tend to outperform the past winners in the long-term. However, Novy-Marx (2012) shows that momentum is driven by past returns over an intermediate-term 12 to seven months prior to momentum portfolio formation. Novy-Marx (2012) suggests excluding the most recent six months from the ranking period as the results show that momentum strategies that are based on the intermediate past returns earn significantly higher profits than strategies that are based on the short-term past returns. The results in Novy-Marx (2012) also show that intermediate past performance is especially strong in the largest and most liquid stocks and applies beyond U.S. equities to international equity indices, commodities, and currencies.

Jegadeesh and Titman (1993) proved the existence of momentum effect by analyzing NYSE and AMEX stocks (Shefrin 2002). Many other types of researches have been done to examine the existence of momentum effect in other markets. For instance, Geert Rouwenhorst (1998) found that medium-term returns are continuous in international equity markets. He examined 12 different European equity markets by using data from 2190 different firms between 1978 and 1995. The portfolios were internationally diversified, and the winner portfolio achieved risk-adjusted returns more than 1 percent per month than the loser portfolio. Results also showed that the continuous pattern of returns was similar in every examined country and that it exists in both small and large firms, although it was weaker for larger firms than small firms. Geert Rouwenhorst's (1998) findings from the European market were highly correlated with the findings from the U.S. market by Jegadeesh and Titman (1993). (Rouwenhorst 1998.)

Doukas and McKnight (2005) confirmed Rouwenhorst's (1998) findings in their research where they examined 13 European stock markets. They found that stock returns are continuous and related to past performance during the 1988-2001 period in the sample. The continuous pattern of the stock returns was significant in 8 of 13 countries but was not limited to a specific country. The research also documented that momentum is linked with size and analyst coverage. Stocks that have low analyst coverage works better in momentum strategies (Doukas & McKnight 2005). Griffin, Ji & Martin (2003) discovered large momentum profits when they examined international data from 40 different countries. Results suggested that the risk is confined to individual countries if the momentum is considered to be driven by risk. In all macroeconomic states, the momentum strategies were profitable. They also proved that the international momentum profits reverse over a longer horizon (Griffin, Ji, & Martin 2003).

Hameed & Kusnadi (2002) documented momentum strategy profits in six Asian stock markets. They formed similar momentum strategies than in Jegadeesh and Titman (1993) and Rouwenhorst (1998), with stocks traded on Hong Kong, Malaysia, Singapore, South Korea, Taiwan, and Thailand markets from 1981 through 1994. No evidence was found to prove the existence of momentum prices in emerging Asian stock markets. Although, when the portfolio weights were spread regionally the portfolio achieved an average positive return of 0.37% per month. However, the profits diminish when the size and turnover effects were controlled. According to Hameed & Kusnadi (2002) in different markets, the influence of the risk factors that drive price momentum is different if momentum prices are explained with differences in risk. (Hameed & Kusnadi 2002.)

Chan, Hameed & Tong (2000) implemented the momentum strategy on international stock market indices in their study: “the profitability of momentum strategies in the international equity markets”. The study covered 23 indices from several different countries. The data included Canada, USA, South Africa, Australia, and 11 countries from Europe, and 8 from Asia. They discovered significant momentum profits especially when the holding period was less than four weeks. When momentum profits were adjusted for the beta risk the evidence suggested that the profits reduce considerably in emerging markets. Results also showed that the momentum profits were larger on markets that had experienced an increase in trading volume in the past. (Chan, Hameed, & Tong 2000.)

Momentum has been proven to be prevailing and strong also across different asset classes. For instance, Jostova, Nikolova, Philipov & Stahel (2013) document strong evidence of momentum profitability in U.S corporate bonds by investigating a sample of 81,491 corporate bonds from 1973 to 2011. According to their result momentum increased over time together with the corporate bond market as the past six month winners earned 0.59% higher average returns over a six month holding period than the losers between 1991 and 2011 (Jostova et al. 2019). Beyhaghi, & Ehsani (2017) find 1.22% monthly momentum premiums among loan characteristics such as spread-to-maturity, credit rating, volatility, liquidity. Moreover, momentum is stronger in loans issued by borrowers with low ratings (Beyhaghi, & Ehsani 2017). Momentum strategies are also documented to be profitable in credit default swap (CDS) contracts. Lee, Naranjom & Sirmans (2014) study 5-year CDS contracts on 1,247 U.S firms from 2003-2011 and show that CDS momentum strategies with a 3-month ranking period and 1-month holding period are able to achieve monthly returns of 0.52%. They furthermore show that past CDS return signals can aid stock momentum strategies to avoid losses and enhance their profits during the financial crisis period (Lee, Naranjo, & Sirmans 2014).

Carhart (1997) extends momentum studies to mutual funds. Momentum strategies that buy one-year prior winner mutual funds and sell losers yields an annual return of 8% and is driven by strong underperformance of the worst mutual funds (Carhart 1997). Jagannathan, Malakhov, & Novikov (2010) examine the performance of hedge funds and find evidence that prior performance can predict future performance. Momentum portfolios that invest in best hedge funds based on past performance provide significant alphas. The loser portfolio consisting of worst hedge funds based on past performance fails to provide significant alphas (Jagannathan et al. 2010). The results in Jagannathan et al. (2010) provide support to the argument that skilled hedge fund managers can produce significantly higher alphas.

Menkhoff, Sarno, Schmeling & Schrimpf (2012) find momentum in currencies by examining the relationship between global foreign exchange volatility risk and cross-section excess returns of carry trade strategies that borrow currencies with a low-interest rate and invest in currencies with a high-interest rate. Menkhoff et al. (2012) show that the relation between the global foreign exchange volatility risk and high-interest rate currencies is negative. Thus, during times of high volatility, the carry trade is performing poorly as the high-interest currencies yield negative returns and low-interest-rate currencies earn positive returns. The results presented in Menkhoff et al. (2012) imply that time-varying risk can explain the excess returns of carry trades in currencies.

Moskowitz, Ooi & Pedersen (2012) find that momentum strategies generate significant abnormal returns that standard asset pricing factors fail to capture in equity indices, currencies, commodities, and bond futures across different markets. Moskowitz et al. (2012) use a time-series momentum method in portfolio formation that differs from the relative-strength or cross-sectional method used in Jegadeesh & Titman (1993). Relative-strength momentum forms portfolios based on the past relative returns of securities as the decision of long and short positions are made by the ranking of the securities past returns. Whereas time-series momentum simply focuses only on security's own past returns instead of relative returns in the cross-section and buys securities if the past return is positive and sells if the past return is negative (Moskowitz et al. 2012).

Asness et al. (2013) show that value and momentum are everywhere by conducting a comprehensive study across eight different markets and asset classes. They find consistent value and momentum returns across individual stocks, country index futures, government bonds, currencies, and commodities. Asness et al. (2013) study value and momentum jointly and find that they are negatively correlated with each other but exhibit stronger correlation across asset classes than passive exposures to the asset classes. Asness et al. (2013) further argue that value and momentum across asset classes are driven by a common global funding liquidity risk that poses challenges to earlier behavioral and rational asset pricing theories that are based on U.S. equities.

Moskowitz & Grinblatt (1999) show that momentum strategies are profitable among industries. Momentum strategies that buy stocks from past winning industries and sell stocks from past losing industries provide significantly higher profits than traditional momentum strategies that buy or sell individual stocks based on their past returns. They also showed that the cross-sectional differences in mean returns or momentum in individual stocks don’t explain the returns of industry momentum. The results indicate that industry momentum strategies are more easily to be implemented than individual stock strategies. Unlike individual stock momentum strategies which performance tend to be driven from the short positions taken by the winner-loser portfolio, industry momentum strategies generate profits almost equally from the long positions as from the short positions. (Moskowitz & Grinblatt 1999.)

More recent studies conducted by Arnott, Clements, Kalesnik & Linnainmaa (2019) and Ehsani & Linnainmaa (2019) argue that industry and stock momentums stem from factor momentum. Arnott et al. (2019) use 51 different factors that have a solid theoretical background to form 36 relative-strength momentum strategies. Factor momentum strategy that takes long in factors with high past one-month returns and short in factors with low past one-month returns yields an annual average return of 10.5%. Whereas the same industry momentum strategy yields an average return of 6.4%. According to the results in Arnott et al. (2019) factor momentum is most profitable with one-month ranking and holding periods similar to industry momentum. All of the strategies considered in Arnott et al. (2019) can provide statistically significant abnormal returns from the Fama-French five-factor model. Arnott et al. (2019) further show that factor momentum is not dependent on the choice of factors and that almost any set of factors exhibit momentum. A momentum strategy that uses only the factors of the Fama-French five-factor model earns an average annual return of 8.0%. (Arnott et al. 2019.)

By using industry neutral-factors Arnott et al. (2019) are able to show that the returns of industry momentum can be explained through the differences in industries’ factor loadings. Arnott et al. (2019) can explain industry momentum through relative-strength factor momentum but not the individual stock momentum. However, Ehsani & Linnainmaa (2019) argue that they can explain all forms of individual stock momentum through time-series factor momentum. Ehsani & Linnainmaa (2019) examine time-series factor momentum through 20 different factors and show that stock momentum strategies are profitable when the factors are autocorrelated and when the autocorrelation breaks down stock momentum profits vanish. Ehsani & Linnainmaa (2019) further show that time-series momentum outperforms relative-strength strategies as time-series directly invest in the positive autocorrelation in factor returns. Ehsani & Linnainmaa (2019) propose based on their results that momentum is not a distinct risk factor as momentum aggregates the autocorrelation found in all factors.

The findings of Arnott et al. (2019) and Ehsani & Linnainmaa (2019) provide strong motivation and support for this thesis to implement momentum strategies in smart beta ETFs. Furthermore, these findings of factor momentum pose a challenge to theories that try to explain momentum. As Arnot et al. (2019) and Ehsani & Linnainmaa (2019) suggest that momentum cannot be explained through the underreaction to the industry or stock-specific news if stock and industry momentums are by-products of factor momentum. Instead of underreaction, they propose that factor momentum could emerge from common shocks to mispricing.

4.1 Explanations for momentum effect

As described above momentum is a well-recognized phenomenon in financial literature and there is no doubt about its existence across different markets and asset classes. Momentum has become well studied and explored empirical fact among academics and practitioners since its discovery over 20 years ago. Even though momentums strong proven presence there is a lot of discussion in financial literature on what can explain this anomaly. (Moskowitz 2010.)

The explanations that have been established can be divided into rational theories and behavioral theories. Where rational theorists suggest that momentum can be explained by risk. They claim that under the efficient market theory the abnormal momentum profits are compensation for higher risk. Behavioral explanations base their theory on behavioral models where prices either underreact or overreact to information. (Moskowitz 2010.)

4.1.1 Rational explanations

Rational theories argue that the profitability of momentum strategies is compensation for risk. These theories are based on the efficient market theory and for the assumption that after positive returns the risk of an asset should increase. Rational models try to explain momentum through economic risks that affect on company's investment and growth rates which influence the company's long-term cash flows and dividends. (Moskowitz 2010.)

One rational explanation for the profitability of momentum strategies has been presented by Conrad & Kaul (1998). According to them the profitability of momentum strategies can be explained by the cross-sectional dispersion in the mean returns of the stocks that have been selected for the momentum strategy portfolio. This theory lays on the assumption that during the implementing period of the strategies the mean returns are constant. They found that contrarian strategies tend to buy (sell) stocks with low (high) mean returns whereas momentum strategies tend to buy (sell) stocks with high (low) mean returns. Conrad & Kaul (1998) claim that momentum profits are compensation for obtaining higher risk as the cross-sectional differences in the mean returns are not related to the returns in time-series patterns. (Conrad & Kaul 1998.)

Johnson's (2002) rational explanation for the success of momentum strategies was his findings of the strong positive correlation between past returns and future expected returns when the expected dividend growth rate change over time. A positive shock to returns implicates to investors that the firm's future cash-flow growth expectations have increased which causes also an increase in the firm's future expected return (Moskowitz 2010).

According to Chordia & Shivakumar (2002), momentum profits can be explained by macroeconomic risk. They suggested that stock returns can be predicted by macroeconomic variables that are able to capture time-varying returns and that the momentum profits are a result of the cross-sectional differences in conditionally expected returns.

Holden & Subrahmanyam (2002) created a model where risk-averse investors receive news event information sequentially to rationalize the continuation of stock returns in the medium term. They argue that momentum profits will exist if a large number of investors are well informed due to the suitably low costs of information and if the information's variance is suitably high. As more investors get better informed and acknowledged on the news events over time, the positive autocorrelation in risk premia can explain the continuation of stock returns. (Holden & Subrahmanyam 2002.)

Sagi & Seasholes (2007) justify momentum profits by analyzing firm-specific attributes such as growth options, costs, and revenues. Firms' return autocorrelation dynamics can be determined by combining these attributes. Return autocorrelation is higher among firms that have better growth options than firms that have poorer growth options. A large part of the firms' value is based on the growth options that they possess. Past winners tend to have better opportunities to implement growth options therefore past winners contain higher risk because growth options are risky assets. These high market-to-book firms have also higher expected returns and they generate approximately 10% higher momentum profits per year than low market-to-book firms. Also, firms implement their growth options more likely during up markets than during down markets. Hence the autocorrelation of returns increases during up markets and decreases in down markets. (Sagi & Seasholes 2007.)

In the model presented by Sagis & Seasholes (2007), the return autocorrelation can become negative due to leverage caused by the firm's costs. When a firm with fixed costs confronts an increase in revenues its profit margins and stock price rise. Low cost (high margin) firms decrease in risk and expected returns are weaker than in high cost (low margin) firms. Results show that low cost (high margin) firms achieve from 2% to 9% higher momentum profits than high cost (low margin) firms. (Sagi & Seasholes 2007.)

Diffusion in expected returns is much higher in firms with high revenue volatility than in firms with low revenue volatility. Expected returns are higher in past winners than in past losers. In a sample of firms with high revenue volatility, the difference in expected returns between past winners and past losers is higher. Momentum profits are from 6% to 14% higher per year in firms with high revenue volatility than in firms with low revenue volatility. (Sagi & Seasholes 2007.)

4.1.2 Behavioral explanations

Behavioral theories explain momentum by non-risk factors that are based on investors' behavior. These theories can be divided into two groups. Some argue that momentum is driven by underreaction and others argue that it is driven by overreaction. Underreaction theories show that stock prices adjust slowly to new information. As the overreaction theories explain momentum by investors who create positive feedback when they overreact to new information which pushes stock prices further away from its fundamental level. These two theories don't cancel each other out. Instead, overreaction and underreaction can work together and be present at the same time to reinforce the momentum effect. Stock prices may be first adjusting slowly to new information to start momentum. Then investors' overreaction may support and strengthen the momentum effect to continue even further. (Moskowitz 2010.)

Chan, Jegadeesh & Lakonishok (1996) challenges the rational risk-based theories by the fact that winner stocks' profits are high only for the first year and that the profits are closer to average during the second and third year. They offer an explanation for the profitability of momentum strategies through the market's underreaction to new information by examining earnings announcements effect to stock prices.

They find that in the first six months most of the momentum returns are achieved around earnings announcements dates. After good or bad earnings announcement markets on average tend to follow the direction shown by the earnings news at least over the next two following announcements. However, earnings news is not the only information that affects stock returns. For example, new equity issues, insider trading, and stock buybacks have their own effects. Analysts' conservatism on adjusting their forecasts gives additional evidence considering market underreaction. Markets may have a hard time to adjust to new information because of slow reassessment of forecasts. Reassessment of forecasts is especially slow among the worst companies. (Chan et al. 1996.)

Evidence presented by Barberis, Shleifer & Vishny (1998) also shows that stock prices underreact to the news in 1-12 months horizon. Over these horizons, positive autocorrelations can be observed because stock prices adjust slowly to the news. In other words, future positive returns can be predicted by today's good news. These findings are inconsistent with the efficient market theory because individual investors who exploit the market's underreaction can achieve high abnormal returns without taking more risk. Their model is based on the assumption presented by Griffin & Tversky (1992) that underreaction occurs when people respect information's strength more than its weight. Earnings announcements are seen as information with low strength and substantial statistical weight and therefore stocks prices tend to underreact to these announcements. (Barberis et al. 1998.)

Results documented by Barberis et al. (1998) show that underreaction is mainly due to representativeness and conservatism among market participants. According to conservatism, people are slow to adjust their beliefs when new information arises (Edwards 1968). Whereas representativeness is about making decisions based on stereotypes (Shefrin 2002:15). For example, investors may ignore the low probability of the firm's continuous growth and assume that stocks with constant past earnings growth will continue growing also in the future (Barberis et al. 1998).

Hong & Stein (1999) examine markets under- and overreaction by investigating how heterogeneous traders interact with each other. Their model divides these traders into two groups: “news-watchers” and “momentum traders”. Available information can be observed only partly by each trader and therefore all traders from both groups are limitedly rational. News-watchers forecasts don’t contain information about current or past prices and thus their forecasts are only based on signals about future fundamentals. Momentum trader’s limitations are that they can only implement simple strategies that are based on past price changes. The model also assumes that information spreads gradually among news-watchers. (Hong & Stein 1999.)

Through these assumptions, the model shows that information is assimilated slowly into prices and that underreaction occurs when only news-watchers are active. Hence the momentum traders start to make profits by taking advantage of the market’s underreaction because prices are still below from their long-run value even though the news-watchers activity has moved the prices up. Momentum traders increased activity moves prices even higher which attracts more momentum traders to get involved. This will accelerate momentum even more and eventually lead prices to overreact. Therefore, momentum traders who invest in the later stage will lose money because prices are far above their fundamental level. (Hong & Stein 1999.)

Daniel, Hirshleifer & Subrahmanyam (1998) also present a theory to explain momentum through markets under- and overreaction. They suggest that under- and overreactions occur due to investors’ overconfidence and changes in confidence. Overconfident investor tends to emphasize the importance of his private information signal and to underestimate public information signals. In particular, when an investor has been personally involved to produce information, he tends to be overconfident about this information but not public information. Thus, stock prices will overreact to the private information signals and underreact to public information signals. Overreaction will cause stock prices to rise too high from their fundamentals. Eventually, prices will move closer to their fundamental level when more and more public information arrives in the market. (Daniel et al. 1998.)

Investors' confidence in their own skills changes in a biased manner from the outcomes of their investment decisions. Public signals can have a confirming effect for investors who trade based on private signals. For example, when good public news arrives after investors' buying decision it tends to increase investors' confidence in their own skills. Interestingly though disconfirming public news has only minor effects on investors' confidence. Thus, overreaction started by private information signal can be accelerated by public information signal which will cause the overreaction to continue even further. This will cause momentum in stock prices until it is reversed when public information gradually moves prices towards their fundamental level. (Daniel et al. 1998.)

4.2 Momentum in exchange-traded funds

As discussed earlier many academics have reported significant abnormal momentum returns in common stocks and across different asset classes. Chan et al. (2000) study momentum strategies when investing in international stock market indices and report significant momentum profits. However, these strategies might not be available for individual investors because of the availability of stock index futures or the restrictions on short-selling Chan et al. (2000). However, trading with country exchange-traded funds that track specific country indices provides individual investors an opportunity for easy access to international stock markets (Tse 2015).

Moskowitz & Grinblatt (1999) proved that momentum strategies are more profitable when implemented in industries instead of individual stocks. Strategies that buy stocks from past winner industries and sell stock from past losing industries earn significantly higher abnormal returns than strategies that only consider individual stocks (Moskowitz & Grinblatt 1999). However, some argue that these returns are not really available for individual investors as the implementation of momentum strategies includes trading with high volume which naturally increases the transaction costs. In high volume trading, ETFs are more cost-efficient than individual stocks. This is because the price impact of large trades is less strong in ETFs due to the smaller bid-ask-spreads and higher liquidity of ETFs (De Jong & Rhee 2008). Furthermore, investors are able to reduce transaction costs of momentum strategies as ETF momentum requires less trading than traditional stock momentum.

Most of the earlier studies of ETF momentum focus in country and sector ETFs by the motivation of the significant results presented in Chan et al. (2000) for international stock market indices and in Moskowitz & Grinblatt (1999) for industries. Andreu, Swinkels & Tjong-A-Tjoe (2013) study momentum strategies with country and sector ETFs. Andreu et al. (2013) report 5% annual excess returns for ETF momentum strategies but the result are statistically insignificant. Tse (2015) uses relative-strength and time-series momentum strategies to approach country and sector ETF momentum. Tse (2015) finds no significant momentum profits for relative-strength strategies. Tse (2015) shows that time-series momentum is profitable during the financial crisis period of 2007-2009 but is outperformed by a simple buy-and-hold strategy when the markets started to recover. Du, Denning & Zhao (2014) finds consistent results with Tse (2015) in their paper examining sector ETF momentum.

Andreu et al. (2013) examine 16 country ETFs and 9 sector ETFs. The sample period for the 16 country ETFs covers the years between 1996 and 2009. For the 9 sector ETFs, the sample period is from 1998 to 2009. Country ETFs include the United States, Canada, Hong Kong, Japan, Singapore, Australia, and ten countries from Europe. Andreu et al. (2013) form 16 different strategies from the combinations of 3, 6, 9- and 12-months formation and holding periods. Andreu et al. (2013) report consistent results with Jegadeesh & Titman (1993) as they find that the strategy with the 6-month formation and holding periods is the most profitable for sector ETFs and the second most profitable for country ETFs. Sector ETF strategy providing 0.84% and country ETF strategy providing 0.61% in monthly excess returns. However, the results reported by Andreu et al. (2013)

are not statistically different from zero. This might be due to the relatively short sample period used in the study according to the authors.

Du et al. (2014) examine market states and momentum in sector ETFs. Their paper considers 10 iShares sector ETFs that follow the Dow Jones US Sector Indexes. The sample period is from 2000 to 2011. Du et al. form momentum strategies with formation periods of 1, 3, 6, 9, and 12-months and holding periods of 1 and 6 months. In addition, Du et al. (2014) use strategies that have 1 and 7-months between the formation and holding period. Due et al. (2014) document that sector ETF momentum strategies are not profitable and that momentum does not depend on market states over the sample period.

Tse (2015) studies momentum strategies with stock index exchange-traded funds by examining 14 sector ETFs and 23 country ETFs. The sample period of the 14 sector ETFs covers the years between 1999 and 2014. For the 23 country ETFs the sample period is from 1997 to 2014. The country ETFs included are the same ones as in Andreu et al. (2013) with the addition of Malaysia, Taiwan, South Korea, China, Mexico, Brazil, and South Africa. For the sector ETFs the sample is also similar to Andreu et al. with the addition of five more recent sectors. Tse (2015) forms 25 different relative-strength strategies from the combinations of 1, 3, 6, 9- and 12-months ranking and holding periods. He also uses strategies that skip the most recent months from the ranking period as suggested by Novy-Marx (2012). Tse (2015) also test ETF momentum through time-series momentum strategies. The purpose of implementing time-series strategies is to avoid a high correlation between ETFs that might hinder the profitability of momentum strategies (Tse 2015). Tse (2015) reports insignificant momentum profits for relative-strength strategies. For the time-series momentum strategies Tse (2015) finds momentum profits during the financial crisis but those profits seem to vanish soon after the crisis.

Andreu et al. (2013) show that the cumulative sector ETF momentum returns increase heavily at the start of the 2007 financial crisis and are at its highest at the end of 2009. Tse (2015) presents consistent results with Andreu et al. (2013) proving that ETF momentum strategies are profitable during the financial crisis, but the profits diminish soon after the crisis. Tse (2015) shows that over the sample period both country and sector ETFs strategies are significantly more profitable than the buy-and-hold strategy. However, during the post-crisis period of 2009-2014, the buy-and-hold strategy is able to outperform both momentum strategies. The buy-and-hold strategy is also more profitable than the momentum strategies when the financial crisis period (2007-2009) is excluded from the sample (Tse 2015). On the other hand, these results are in contrast with the findings of Du et al. (2014) who argue that momentum does not depend on market states. One of the aims of this thesis is to provide a closer insight into the ETF momentum performance during the financial crisis with a longer sample than earlier studies.

5 Data and methodology

This chapter describes the data and methodology used to test the hypotheses set out in section 1.1. The sample includes 24 ETFs traded on NYSE Arca, Cboe BZX, and NASDAQ that invest in six different factors. Monthly closing prices of the selected ETFs are retrieved from the Yahoo Finance website (2020). The methodology of this thesis follows the methodology utilized in Tse (2015) in order to ensure the comparability of the results of smart beta ETFs to country and sector ETFs. In total eight different momentum portfolios are constructed based on the past performance of the selected ETFs. Inspired by the findings presented in Arnott et al. (2019) and Ehsani & Linnainmaa (2019), both relative-strength and time-series momentum strategies are considered. The monthly momentum excess returns are adjusted with Fama-French three, five, and six-factor models to test whether abnormal returns can be achieved by implementing momentum strategies in smart beta ETFs. The data for Fama-French factor models are retrieved from Kenneth R. French Data Library (2020).

5.1 Data

Data sample is formed from ETFs that invest in broadly defined factors studied in the academic literature. As of March 2020, there were 401 equity smart beta ETFs available for investors in the U.S. that can be categorized in various ways (ETFdb 2020). For instance, Morningstar (2019) categorizes smart beta ETFs into 11 different strategic-beta groups based on their factor exposure. However, this thesis centers on six common factors: value, size, momentum, low volatility, quality, and growth that are backed by strong theoretical evidence studied in the academic literature and are widely used strategies by hedge funds and active mutual funds. The selection of factors should not affect momentum as Arnott et al. (2019) point out that momentum profits are not dependent on the amount or the selection of the factors. Moreover, these factor ETFs offer longer available sample periods and are more focused on specific factors than the omitted categories.

Table 1 presents the six factors that are used to categorize the smart beta ETFs included in the sample. These factors are identified with a solid theoretical background by academics as discussed in section 2.1. However, it is to be noted that smart beta ETFs are long-only unlike the factors discussed in academic literature even though they try to capture the same factors through different weighting methods. This simplistic factor approach could lead to unintended factor exposures as pointed out by Jacobs & Levy (2014). Value factor takes a long position in high book-to-market firms and a short position in low book-to-market stocks as cheap stocks generate higher returns than expensive stocks (Fama & French 1993; Lakonishok et al. 1994). Value ETFs track indices that are composed of stocks that exhibit value characteristics and are thought to be undervalued compared to other stocks. Size factor tilts towards smaller stocks by buying small stocks and selling large stocks (Banz 1981). Size ETFs seek to track indices with relatively smaller average market capitalization.

As discussed earlier momentum factor takes long and short positions based on stocks past performance (Jegadeesh & Titman 1993). Momentum ETFs offer exposure to stocks with relatively higher price momentum by tracking indices consisted of stocks with high momentum characteristics. Low volatility portfolio yields positive alpha by buying stocks with lower risk and selling stocks with higher risk (Baker et al. 2011; Frazzini & Pedersen 2014). Low volatility ETFs try to capture the results of an index that comprises stocks with lower volatilities than the broader market over the past 12 months. Asness et al. (2019) show that quality portfolios that buy high-quality stocks and sell low-quality stocks can yield significant risk-adjusted returns. Quality ETFs offer exposure to quality stocks through indices that identify stocks as quality stocks by fundamentals such as return-on-equity, earnings variability, and debt-to-equity. A long-short portfolio that buys stocks with good growth characteristics and sells stocks with poor growth characteristics is able to earn significant excess returns (Mohanram 2005). Growth ETFs seek to capture growth factor returns by tracking indices that are comprised of stocks of firms whose earnings are expected to grow at an above-average rate over the market.

Factor	Description	Variables
Value	Buy cheap and sell expensive stocks	Combination of price-to-book and price-to-earnings ratios
Size	Buy small and sell large stocks	Current market capitalisation
Momentum	Buy winners and sell losers	Return over the past 12 months, excluding the most recent month
Low Volatility	Buy less volatile and sell more volatile stocks	Standard deviation over the past 12 months
Quality	Buy high and sell low quality stocks	Combination of return-on-equity and debt-over-equity ratios
Growth	Buy growing and sell declining companies	Combination of 3-year sales per share and earnings per share growth rates

Table 1. Factor groups and definitions (Factor Research 2020).

From all of the available smart beta ETFs in the U.S. market, 133 smart beta ETFs can be identified and categorized into the six groups presented in Table 1 by screening and using information available on online (Yahoo Finance 2020; ETFdb 2020; Factor Research 2020; Morningstar 2019; ETFGI 2020). The number of ETFs identified in each group is as follows: 42 ETFs in value, 13 ETFs in size, 13 ETFs in momentum, 18 ETFs in low volatility, 10 ETFs in quality, and 37 ETFs in the growth group. Similarly to Tse (2015) highly correlated ETFs that represent a similar investment style are excluded from the sample. Thus, in each factor group, the ETFs are divided into subgroups based on the market capitalization that they are tracking (small cap, mid-cap, large cap, and total market cap). Four ETFs that are earliest available and represent different market capitalizations are then selected from each of the factor groups and ultimately included in the sample. Thus, in total, the sample includes 24 ETFs covering all six factors and all four market capitalizations subgroups within each factor group. The described selection procedure is used in order to avoid the sample to consist of multiple ETFs that represent the same factor group and market capitalization.

Table 2 present the smart beta ETFs included in the sample. The monthly mean excess returns of the ETFs from the respective inception date until February 2020 are presented on the fifth column of the table. Most of the ETFs are traded on NYSE Arca except for iShares Edge MSCI U.S.A. Momentum Factor ETF (MTUM), iShares Edge MSCI Min Vol U.S.A. ETF (USMV), and iShares Edge MSCI U.S.A. Quality Factor ETF (QUAL) that are traded on Cboe BZX formerly known as BATS as well as Invesco DWA SmallCap Momentum ETF (DWAS) and iShares Core S&P U.S. Growth ETF (IUSG) that are traded on NASDAQ. Similarly to Tse (2015) the monthly adjusted closing prices from the respective inception dates until February 2020 are retrieved from Yahoo Finance and log returns for each ETF are calculated by the start of the month closing prices. Log returns are used to decrease the skewness in returns distribution and to ensure the comparability of returns in different time periods (Gregory et al. 1997; Jensen 1968; Kreander et al. 2005). Excess returns are calculated with the 1-month Treasury bill rate provided by Ibbotson Associates to the Kenneth R. French Data Library (2020).

For most of the ETFs (10 ETFs), the sample period starts during the second and third quarters of the year 2000. Thus, the sample period for momentum strategies starts at 1.8.2000 when 10 ETFs are available from three different factor groups (Value, Size, and Growth). The other ETFs are included in the sample in accordance with their respective inception dates. After 5.5.2011 all of the factor groups are represented in the ETF universe for momentum strategies. All of the ETFs generated positive returns over the sample period with monthly excess returns varying from 0.254% (IWF) to 1.075% (MTUM). The highest standard deviation is observed from the IJR ETF (8.612%) and the lowest from the USMV ETF (2.691%). All Sharpe ratios are positive varying from 0.052 (IUSV) to 0.362 (USMV).

Ticker	Inception date	Factor	Market cap	Mean (%)	Std (%)	Sharpe ratio	Net Assets (m $)
IWD	22.5.2000	Value	Large Cap	0.383	4.231	0.090	31070
IWN	24.7.2000	Value	Small Cap	0.528	5.320	0.099	6590
IUSV	24.7.2000	Value	Total Market	0.413	4.350	0.095	5250
IJJ	24.7.2000	Value	Mid Cap	0.613	5.006	0.122	3830
IJH	22.5.2000	Size	Mid Cap	0.546	4.918	0.111	35720
IJR	22.5.2000	Size	Small Cap	0.590	8.612	0.069	31820
VXF	27.12.2001	Size	Total Market	0.624	5.017	0.124	53230
SIZE	16.4.2013	Size	Large Cap	0.739	3.439	0.215	978
MTUM	16.4.2013	Momentum	Total Market	1.075	3.445	0.312	8110
XMMO	3.3.2005	Momentum	Mid Cap	0.703	5.057	0.139	474
ONEO	1.12.2015	Momentum	Large Cap	0.428	4.305	0.099	249
DWAS	19.7.2012	Momentum	Small Cap	0.793	5.147	0.154	151
USMV	18.10.2011	Low Volatility	Total Market	0.973	2.691	0.362	30780
SPLV	5.5.2011	Low Volatility	Large Cap	0.877	2.818	0.311	9040
XMLV	12.2.2013	Low Volatility	Mid Cap	0.862	3.244	0.266	2500
XSLV	12.2.2013	Low Volatility	Small Cap	0.817	3.835	0.213	1490
QUAL	16.7.2013	Quality	Total Market	0.838	3.439	0.244	15100
SPHQ	6.12.2005	Quality	Large Cap	0.465	4.467	0.104	1450
XMHQ	1.12.2006	Quality	Mid Cap	0.411	4.943	0.083	21
EES	23.2.2007	Quality	Small cap	0.465	6.115	0.076	420
IWF	22.5.2000	Growth	Large Cap	0.271	4.856	0.056	42450
IWO	24.7.2000	Growth	Small Cap	0.333	6.155	0.054	7020
IUSG	24.7.2000	Growth	Total Market	0.254	4.911	0.052	6870
IJK	24.7.2000	Growth	Mid Cap	0.447	5.140	0.087	5270

Table 2. Data sample of smart beta exchange-traded funds.

The monthly momentum returns are adjusted with Fama-French three, five, and six-factor models to test whether abnormal returns can be observed by implementing momentum strategies in smart beta ETFs. The monthly returns for the market, size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), and momentum (UMD) factors are retrieved from Kenneth French data library for the period of 1.5.2000 – 1.2.2020 (French 2020). Also, the risk-free rate (1-month Treasury bill rate) from 1.5.2000 to 1.2.2020 is retrieved from Kenneth R. French Data Library (2020). The 1-month Treasury bill rate is provided by Ibbotson Associates.

The data sample used in this thesis includes more ETFs and have a longer sample period than earlier studies reported on ETF momentum. As described earlier the sample period spans out from 1.8.2000 to 1.2.2020 providing over 19 years (236 months) of data. However, it is to be noted that the sample includes 10 ETFs at the time of 1.8.2000 and the other ETFs are included in the momentum ETF universe following the respective inception dates. Previous studies on country and sector ETFs have used sample periods varying from 11 years to 18 years. For instance, Andreu et al. (2013) study 16 country ETFs from April 1996 to December 2009 and 9 sector ETFs from December 1998 to December 2009. Du et al. (2014) study 10 sector ETFs from July 2000 to July 2011. Tse (2015) study 23 country ETFs from January 1997 to December 2014 and 14 sector ETFs from January 1999 to December 2014.

The results from both studies Andreu et al. (2013) and Tse (2015) show that ETF momentum strategies are profitable during the financial crisis period of 2007-2009. However, results reported in Tse (2015) show that ETF momentum profits vanish soon after the crisis. The longer sample period used in this study will give a closer insight into momentum profits from the post-crisis period as the sample period includes over five years more data than used in Tse (2015). This thesis forms two subsamples to further investigate the performance of momentum strategies during the financial crisis and post-crisis periods. The financial crisis period is defined to be the period of 1.10.2007-1.3.2009 similar to Tse (2015) and others (Marston 2011; Nofsinger & Varma 2014). Thus, the post-crisis subsample covers the period of 1.3.2009-1.2.2020 whereas the subsample of the financial crisis period is between 1.10.2007 and 1.3.2009.

5.2 Methodology

Similarly to Tse (2015), this thesis examines the profitability of momentum strategies in smart beta ETFs by implementing relative-strength as well as time-series momentum strategies with different ranking and formation periods. Relative-strength or cross-sectional momentum initially documented by Jegadeesh & Titman (1993) forms momentum portfolios based on the past relative returns of securities as the decision of long and short positions is made by the ranking of the securities past returns. Time-series momentum simply focuses only on securities' own past returns instead of relative returns in the cross-section and buys securities if the past return is positive and sells if the past return is negative (Moskowitz et al. 2012).

Moskowitz et al. (2012) find that time-series momentum generates significant abnormal returns in equity indices, currencies, commodities, and bond futures. According to Tse (2015), time-series momentum profits should not be affected by the high cross-market correlations between ETFs due to the fact that time-series momentum is not based on returns of other assets. For similar reasons, this thesis tests the profitability of time-series momentum strategies. Furthermore, including time-series momentum strategies into the scope of this thesis improves the comparability of results to the results reported by Tse (2015) on country and sector ETFs.

In this study, momentum portfolios are formed with five ranking periods (denoted by K) and five holding periods (denoted by H) following the methodology of momentum portfolio formation presented by Jegadeesh & Titman (1993). Ranking and holding periods of 1, 3, 6, 9, and 12 months are considered. In addition, following the findings of Novy-Marx (2012) showing that momentum profits are driven by the past returns from 12 to 7 months, three additional strategies with 1-month holding periods are formed with 12 and 6 months ranking periods and 1 and 7 months between the ranking and holding periods that is denoted by S. Thus, this thesis considers only K=H strategies except for the three additional strategies that exclude one and seven most recent months from the ranking period.

In total eight different momentum strategies are implemented for both relative-strength and time-series momentum methods. For simplicity, the strategies are denoted by K-(S)-H in this thesis. For example, the strategy with the 6 months ranking and 6 months holding period is denoted by (6-6) and the strategy with 12 months ranking period excluding the most recent month with 1 month holding period is denoted by (12-1-1). Thus, the eight strategies considered in this thesis for both relative-strength and time-series momentum are then denoted as follows: (7-1-1), (12-7-1), (12-1-1), (1-1), (3-3), (6-6), (9-9), and (12-12). The reason for forming three different strategies with a 1-month holding period is because factor momentum is at is strongest with a 1-month holding period (Arnott et al. 2019).

In this thesis, the time-series momentum portfolios are simply formed based on individual ETF's past returns. In each month t, the strategy goes long on ETFs that have positive past returns in K months and goes short on ETFs that have negative past return in K months. These positions are held for H months and then closed. For relative-strength momentum strategies, the portfolio formation is conducted similarly to Jegadeesh & Titman (1993). At the beginning of each month t, the ETFs are ranked based on their past returns in K months. The top 10% of ETFs with the highest returns in K months form the winner portfolio and the bottom 10% of ETFs with the lowest returns in K months form the loser portfolio. The amount of ETFs to be included in the portfolios at the beginning of each month t is determined by $N \times 10\%$, where N is the total number of ETFs available at time t. In each month t, the strategy takes a long position in winner portfolio ETFs with equal weights and short position in loser portfolio ETFs with equal weights and hold these positions for K months.

It is to be noted that in any given time t, the strategies hold multiple portfolios H if the holding period is more than one month that results in overlapping observations.

Following the methodology used by Jegdeesh & Titman (1993) and others, a single time series of monthly returns is derived by determining monthly momentum returns by the average of active H strategies with equal weights of $1/H$ (Jegadeesh & Titman 1993; Moskowitz et al. 2012; Tse 2015; Arnott et al. 2019). This procedure is applied in both relative-strength and time-series strategies in order to improve the power of test statistics of the results (Tse 2015).

In relative-strength momentum strategies, many different methods have been utilized to determine the number of stocks to be included in the winner and loser portfolios. Jegadeesh & Titman (1993) invest in the top 10% of the winners and bottom 10% of losers when forming momentum strategies. In previous ETF momentum studies, Andreu et al. (2013) invest in one winner ETF and one loser ETF. Tse (2015) argues that choosing only one ETF to the portfolios with small and short sample might not provide reliable results. Thus, Tse (2015) considers investing in the top and bottom four country ETFs (17%) and in the top and bottom two sector ETFs (14%).

Furthermore, Tse (2015) also applies the proportional weight method used by e.g. Chan et al. (2000) and Lehmann (1990) where securities are held in proportion to their market-adjusted returns. Thus, the proportional weight method considers all assets instead of focusing only on extremes (Lewellen 2002). However, a more recent study published by Bird, Gao & Yeung (2017) show that statistically significant momentum profits diminish when the amount of securities included in the portfolios is increased to cover all of the securities in the investment universe. Furthermore, a higher amount of securities included in the portfolios increases the already high transaction costs of momentum strategies that decrease even further the practical profitability of these strategies. Thus, this thesis follows Jegadeesh & Titman (1993) and invests in the top 10% of the winners and bottom 10% of the losers as the aim of this thesis is to study momentum strategies' profitability.

Motivated by the implications made by Fama & French (2018) about the choice and explanatory power of multifactor asset pricing models this thesis uses regressions of Fama-French three, five, and six-factor models to test the hypothesis presented in chapter 1.1. Previous researches have shown that FF3 and FF5 models are unable to explain momentum returns (Fama & French 1996; 2015; 2017). This means that momentum strategies are able to generate significant alphas from the regressions as the intercept of the regressions is significantly different from zero. Thus, in order to reject the null hypothesis, significant positive alphas should be observed from all of the three different factor models when the monthly excess momentum returns are computed to regressions as a dependent variable.

To test the hypothesis presented in chapter 1.1 alphas of the smart beta ETF momentum strategies are computed from the following regressions:

$$R_{mom} = \alpha + \beta_1 (R_M - R_f) + \beta_2 SMB + \beta_3 HML + \varepsilon \tag{5}$$

$$R_{mom} = \alpha + \beta_1 (R_M - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon \tag{6}$$

$$R_{mom} = \alpha + \beta_1 (R_M - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \beta_6 UMD + \varepsilon \tag{7}$$

Where R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $(R_M - R_f)$ is the risk-adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return, RMW is the difference of returns between stocks with robust profitability and stocks with low profitability, CMA is the difference of returns between stocks of high investment firms and stocks of low investment firms, UMD is the difference of returns between two high prior return portfolios and two low prior return portfolios, ε is the zero mean residual. (Fama & French 2018.)

6 Results

This chapter presents and discusses the empirical results of smart beta ETF momentum strategies considered in this thesis. First, the results from relative-strength strategies are discussed. The descriptive statistics for all eight momentum strategies implemented in the study are presented as well as the empirical results from the three regressions described in the previous chapter. Later, the results from time-series momentum strategies are presented and discussed in the same manner. Furthermore, the results are compared against previous results documented in the academic literature.

6.1 Relative-strength momentum

Table 3 reports the average monthly excess returns, standard deviations, and Sharpe ratios of the eight different relative-strength momentum strategies implemented in smart beta ETFs. In addition to winner-loser portfolios, Table 3 also reports the statistics from the long-only and short-only portfolios in order to have further implications about the drivers of momentum strategies.

Table 3 shows that only the (6-6) and (9-9) strategies are able to yield positive average returns over the sample period. The average returns vary from -0.445% to 0.076% where the highest return is observed from the (6-6) strategy and the lowest return from the (1-1) strategy. The poor performance of relative-strength strategies is obvious as the only positive returns of 0.0076% from strategy (6-6) and 0.005% from strategy (9-9) are economically insignificant in magnitude. Furthermore, the Sharpe ratios of the (6-6) and (9-9) strategies are only 0.029 and 0.002 respectively. Standard deviations of the strategies vary between 2.4% and 4.3% where the (12-12) strategy has the lowest standard deviation and the (1-1) strategy the highest. The Sharpe ratios of the winner-loser momentum portfolios are all negative over the sample period except for the (6-6) and (9-9) strategies. The lowest Sharpe ratio of -0.105 is observed from the (1-1) strategy and the highest Sharpe ratio of 0.029 from the (6-6) strategy.

Relative-strength momentum

Strategy: K-(S)-H	W-L Portfolio	Long Portfolio	Short Portfolio
7-1-1			
Mean %	-0.185	0.473	-0.772
Standard deviation %	3.050	5.002	4.849
Sharpe ratio	-0.061	0.094	-0.159
12-1-1			
Mean %	-0.100	0.534	-0.743
Standard deviation %	3.150	5.182	4.764
Sharpe ratio	-0.032	0.103	-0.156
12-7-1			
Mean %	-0.054	0.507	-0.669
Standard deviation %	2.901	5.060	4.910
Sharpe ratio	-0.019	0.100	-0.136
1-1			
Mean %	-0.445	0.189	-0.758
Standard deviation %	4.257	5.380	5.380
Sharpe ratio	-0.105	0.035	-0.141
3-3			
Mean %	-0.206	0.311	-0.637
Standard deviation %	3.218	4.868	5.224
Sharpe ratio	-0.064	0.064	-0.122
6-6			
Mean %	0.076	0.527	-0.566
Standard deviation %	2.673	4.986	4.920
Sharpe ratio	0.029	0.106	-0.115
9-9			
Mean %	0.005	0.518	-0.624
Standard deviation %	2.507	4.983	4.622
Sharpe ratio	0.002	0.104	-0.135
12-12			
Mean %	-0.061	0.504	-0.674
Standard deviation %	2.446	4.997	4.761
Sharpe ratio	-0.025	0.101	-0.142

Table 3. Returns and descriptive statistics of relative-strength momentum.
The table reports the average monthly excess returns, standard deviations, and Sharpe ratios of relative-strength momentum strategies over the whole sample period 1.8.2000-1.2.2020. Strategies are denoted by K-(S)-H where K is the ranking period, S is the months skipped between

the ranking and holding periods, H is the holding period. The first column reports the results from winner-loser portfolios, the second column from the long-only portfolios, and the third from the short-only portfolios. The results from the short-only portfolios are presented in terms of the short position in the underlying ETFs in the portfolio. The excess returns are computed with the 1-month Treasury bill rate retrieved from Kenneth R. French Data Library (2020) provided by Ibbotson Associates.

The weak performance of relative-strength momentum strategies over the sample period is clearly driven by the poor performance of the short portfolios. All of the short-only portfolios yield negative average monthly excess returns varying from -0.772% to -0.566% where the (7-1-1) strategy yields the lowest return and the (6-6) the highest return. Table 4 shows that the short portfolios actually yield similar positive returns than the long portfolios over the sample period and thus weakens the performance of the winner-loser portfolios. This implicates that the relative prior returns of the smart beta ETFs do not predict future returns.

All of the long portfolios yield positive returns where the (12-1-1) strategy is the most profitable with a return of 0.534% and the (1-1) strategy yields the lowest return of 0.189%. The highest Sharpe ratio in short portfolios is observed from the strategy the (6-6) strategy with the Sharpe ratio of -0.115 and in long portfolios from the (12-1-1) strategy with a Sharpe ratio of 0.103. The lowest Sharpe ratio in short portfolios is -0.159 with the (7-1-1) strategy and in long portfolios, the lowest Sharpe ratio is 0.035 with the (1-1) strategy. The standard deviations of short portfolios vary between 4.6% and 5.4% while the standard deviations of long portfolios vary between 4.9% and 5.4%.

Similarly to Tse (2015), this thesis reports economically insignificant monthly average returns for relative-strength ETF momentum strategies. Tse (2015) reports less than 0.6% monthly momentum profits for all of the strategies considered in the study for the country and sector ETFs. The returns presented in Table 3 for smart beta ETFs are weaker than the returns reported in previous studies on ETF momentum in country and sector ETFs (see Andreu et al. 2013; Du et al. 2014; Tse 2015). For instance, considering the most profitable strategy (6-6) that provides a monthly return of 0.076% compared to the return of 0.564% from the same strategy in sector ETFs documented in Tse (2015).

Moreover, the monthly returns are in sharp contrast with results reported by Arnott et al. (2019), who for example report a 0.67% monthly average return for a momentum strategy that rotates the five factors of Fama-French 5-factor model in the universe of stocks.

Correspondingly to Tse (2015) the difference between the winner ETFs and loser ETFs is small as the ETFs are highly correlated with each other. Tse (2015) reports a 0.607% monthly return for the (6-6) long portfolio and a 0.477% return for the (6-6) short portfolio. The small difference between the winners and losers documented in this thesis is also consistent with the findings of Israel & Moskowitz (2013) who show that the returns of momentum, value, and size long-short portfolios are driven by the long-only portfolio.

Table 4 reports the results of the Fama-French 3-factor model regression set out in equation 5 for the eight different relative-strength momentum strategies implemented in smart beta ETFs. In addition to winner-loser portfolios, Table 4 also reports the results of Fama-French 3-factor model regression for the top 10% long portfolios and bottom 10% short portfolios in order to have further implications about the drivers of momentum strategies.

As expected from the results of Table 3, all of the strategies are unable to provide positive abnormal returns when the monthly excess returns are regressed against the FF3 model. For all momentum strategies, all intercepts (alphas) are statistically not different from zero. In Table 4 the highest and only positive abnormal monthly average return of 0.1% (p-value 0.682) can be observed from the (6-6) strategy. However, the positive return is statistically insignificant as the p-value is higher than the acceptable 5% significance level. In general, the three factors of the model are not able to explain the excess returns of the momentum strategies as in most cases the p-values of the factor coefficients are above the 5% significance level. The size factor is able to explain the returns at 5% significance level in (12-12), (9-9), and (6-6) strategies with the factor loading varying from 0.206 to 0.264 implying that the returns of these strategies can be explained by small firms. However, the capability of the model to explain momentum excess returns is rather weak as the R-squares vary from 0.015 to 0.100.

Fama-French 3-Factor (relative-strength momentum)

Strategy:	W-L	Long	Short	**Strategy:**	W-L	Long	Short
7-1-1				**3-3**			
Alpha	-0.002	-0.002	-0.001	Alpha	-0.002	-0.002	-0.001
	(0.349)	(0.231)	(0.215)		(0.402)	(0.085)	(0.566)
Rm - Rf	-0.028	**0.970**	**-0.995**	Rm - Rf	**-0.152**	**0.927**	**-1.075**
	(0.571)	**(0.000)**	**(0.000)**		**(0.002)**	**(0.000)**	**(0.000)**
SMB	0.117	**0.434**	**-0.316**	SMB	0.058	**0.374**	**-0.318**
	(0.17)	**(0.000)**	**(0.000)**		(0.498)	**(0.000)**	**(0.000)**
HML	0.118	0.080	0.036	HML	**0.262**	**0.148**	**0.108**
	(0.125)	(0.113)	(0.428)		**(0.000)**	**(0.001)**	**(0.003)**
R-square	0.019	0.845	0.868	R-square	0.094	0.830	0.907
12-1-1				**6-6**			
Alpha	-0.002	-0.001	-0.001	Alpha	0.001	-0.001	0.000
	(0.481)	(0.271)	(0.323)		(0.682)	(0.541)	(0.796)
Rm - Rf	0.051	**1.026**	**-0.972**	Rm - Rf	**-0.084**	**0.965**	**-1.045**
	(0.338)	**(0.000)**	**(0.000)**		**(0.042)**	**(0.000)**	**(0.000)**
SMB	0.105	**0.438**	**-0.331**	SMB	**0.206**	**0.479**	**-0.273**
	(0.246)	**(0.000)**	**(0.000)**		**(0.004)**	**(0.000)**	**(0.000)**
HML	-0.031	0.012	-0.045	HML	**0.234**	**0.116**	**0.114**
	(0.71)	(0.817)	(0.315)		**(0.000)**	**(0.006)**	**(0.001)**
R-square	0.015	0.856	0.876	R-square	0.100	0.881	0.924
12-7-1				**9-9**			
Alpha	-0.001	-0.002	0.000	Alpha	0.000	-0.001	0.000
	(0.636)	(0.162)	(0.798)		(0.804)	(0.211)	(0.862)
Rm - Rf	0.003	**1.003**	**-0.997**	Rm - Rf	-0.001	**0.996**	**-0.995**
	(0.952)	**(0.000)**	**(0.000)**		(0.972)	**(0.000)**	**(0.000)**
SMB	0.153	**0.481**	**-0.326**	SMB	**0.234**	**0.475**	**-0.241**
	(0.065)	**(0.000)**	**(0.000)**		**(0.001)**	**(0.000)**	**(0.000)**
HML	**-0.153**	-0.044	**-0.111**	HML	-0.024	0.027	-0.053
	(0.044)	(0.355)	**(0.018)**		(0.712)	(0.53)	(0.121)
R-square	0.032	0.873	0.874	R-square	0.054	0.892	0.920
1-1				**12-12**			
Alpha	-0.004	-0.003	-0.002	Alpha	-0.001	-0.002	0.000
	(0.146)	(0.157)	(0.082)		(0.541)	(0.098)	(0.711)
Rm - Rf	**-0.174**	**0.908**	**-1.077**	Rm - Rf	-0.026	**1.002**	**-1.025**
	(0.009)	**(0.000)**	**(0.000)**		(0.525)	**(0.000)**	**(0.000)**
SMB	-0.027	**0.329**	**-0.356**	SMB	**0.264**	**0.491**	**-0.226**
	(0.816)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	**0.236**	**0.181**	0.046	HML	-0.078	-0.019	-0.061
	(0.011)	**(0.013)**	(0.276)		(0.215)	(0.645)	(0.087)
R-square	0.060	0.642	0.875	R-square	0.069	0.904	0.921

Table 4. Results of relative-strength momentum from the FF3 model regression.
The table reports the results of relative-strength momentum from the Fama-French 3-factor model regression over the sample period of 1.8.2000-1.2.2020. The first column presents the results from the winner-loser momentum portfolios, the second column from the long-only portfolios, and the third column from the short-only portfolios. The results are computed as set out in equation 5 where the dependent variable R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $(R_M - R_f)$ is the risk-adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return. The p-values of the respective coefficients are reported in parentheses and the significance levels at the 5% are bolded.

None of the long-only or short-only portfolios are able to generate significant alphas. Similarly to the winner-loser portfolio, all intercepts are insignificant and close to zero. The FF3 model's capability to explain long and short portfolios is much better than in winner-loser portfolios. In most cases, the factor coefficients are significant at the 5% level. For instance, the market factor is significant in all cases with the factor loading varying from 0.908 to 1.026 in long portfolios and from -1.075 to -0.972 in short portfolios implying that the returns of long and short portfolios strongly co-move with the market. This is consistent with the fact that the ETFs used in the sample comprises a large part of the total market capitalization in the US market. Moreover, the explanatory power of the model is much higher for the long and short portfolios than for the winner-loser portfolio as the R-squares vary from 0.642 to 0.928.

Table 5 reports the results of the Fama-French 5-factor model regression set out in equation 6 for the relative-strength ETF momentum strategies over the sample period. Table 5 shows that the intercepts for all momentum strategies are negative and statistically insignificant at the 5% significance level except for the (1-1) strategy. However, the significant average monthly return for the (1-1) strategy is negative 0.6%. Similarly to the FF3 model the FF5 model is not able to explain the excess returns of the momentum strategies in general as in most cases the p-values of the factor coefficients are above the 5% significance level and R-squares are low varying from 0.029 to 0.166. For instance, in strategies (7-1-1), (12-1-1), and (1-1) all factor coefficients are insignificant at the 5% level. However, the added factor RMW is able to capture momentum returns in four out of eight strategies that emphasize the importance of the factor.

Fama-French 5-Factor (relative-strength momentum)

Strategy:	W-L	Long	Short	**Strategy:**	W-L	Long	Short
7-1-1				**3-3**			
Alpha	-0.003	-0.002	-0.002	Alpha	-0.004	**-0.003**	-0.001
	(0.157)	(0.112)	(0.115)		(0.098)	**(0.013)**	(0.263)
Rm - Rf	0.021	**0.994**	**-0.969**	Rm - Rf	-0.069	**0.976**	**-1.041**
	(0.714)	**(0.000)**	**(0.000)**		(0.236)	**(0.000)**	**(0.000)**
SMB	0.149	**0.448**	**-0.299**	SMB	0.107	**0.406**	**-0.303**
	(0.089)	**(0.000)**	**(0.000)**		(0.214)	**(0.000)**	**(0.000)**
HML	0.018	-0.034	0.048	HML	0.058	-0.019	0.071
	(0.85)	(0.58)	(0.382)		(0.533)	(0.759)	(0.146)
RMW	0.170	0.082	0.087	RMW	0.205	0.132	0.069

	(0.151)	(0.288)	(0.208)		(0.067)	(0.072)	(0.237)
CMA	0.163	0.092	0.073	CMA	**0.339**	0.161	**0.179**
	(0.249)	(0.322)	(0.375)		**(0.012)**	(0.066)	**(0.011)**
R-square	0.035	0.847	0.869	R-square	0.134	0.837	0.909
12-1-1				**6-6**			
Alpha	-0.003	-0.002	-0.001	Alpha	-0.001	-0.002	-0.001
	(0.254)	(0.122)	(0.212)		(0.419)	(0.125)	(0.43)
Rm - Rf	0.099	**1.053**	**-0.951**	Rm - Rf	0.007	**1.009**	**-0.998**
	(0.108)	**(0.000)**	**(0.000)**		(0.875)	**(0.000)**	**(0.000)**
SMB	0.150	**0.464**	**-0.313**	SMB	**0.287**	**0.516**	**-0.230**
	(0.11)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	-0.087	-0.096	0.006	HML	0.068	-0.037	**0.101**
	(0.379)	(0.121)	(0.905)		(0.375)	(0.471)	**(0.016)**
RMW	0.216	0.120	0.097	RMW	**0.334**	**0.154**	**0.178**
	(0.088)	(0.129)	(0.154)		**(0.001)**	**(0.018)**	**(0.001)**
CMA	0.042	0.081	-0.037	CMA	0.177	0.108	0.069
	(0.776)	(0.384)	(0.643)		(0.119)	(0.159)	(0.268)
R-square	0.029	0.859	0.877	R-square	0.166	0.889	0.926
12-7-1				**9-9**			
Alpha	-0.002	-0.002	-0.001	Alpha	-0.002	**-0.002**	-0.001
	(0.273)	(0.062)	(0.443)		(0.241)	**(0.039)**	(0.404)
Rm - Rf	0.063	**1.027**	**-0.961**	Rm - Rf	0.067	**1.033**	**-0.963**
	(0.257)	**(0.000)**	**(0.000)**		(0.154)	**(0.000)**	**(0.000)**
SMB	**0.203**	**0.508**	**-0.303**	SMB	**0.294**	**0.508**	**-0.214**
	(0.017)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	**-0.234**	**-0.162**	-0.075	HML	-0.130	**-0.108**	-0.026
	(0.01)	**(0.005)**	(0.172)		(0.085)	**(0.033)**	(0.527)
RMW	**0.260**	0.111	**0.151**	RMW	**0.292**	**0.148**	**0.143**
	(0.023)	(0.125)	**(0.032)**		**(0.002)**	**(0.019)**	**(0.006)**
CMA	0.081	0.090	-0.008	CMA	0.087	0.117	-0.029
	(0.549)	(0.288)	(0.922)		(0.44)	(0.121)	(0.64)
R-square	0.058	0.877	0.877	R-square	0.100	0.898	0.922
1-1				**12-12**			
Alpha	**-0.006**	-0.004	**-0.003**	Alpha	-0.002	**-0.003**	-0.001
	(0.046)	(0.078)	**(0.025)**		(0.149)	**(0.017)**	(0.332)
Rm - Rf	-0.091	**0.947**	**-1.035**	Rm - Rf	0.040	**1.037**	**-0.994**
	(0.247)	**(0.000)**	**(0.000)**		(0.385)	**(0.000)**	**(0.000)**
SMB	0.008	**0.348**	**-0.343**	SMB	**0.298**	**0.515**	**-0.216**
	(0.948)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	0.054	0.027	0.021	HML	**-0.214**	**-0.156**	-0.062
	(0.671)	(0.783)	(0.721)		**(0.004)**	**(0.001)**	(0.142)
RMW	0.192	0.085	0.100	RMW	**0.240**	**0.134**	**0.106**
	(0.193)	(0.461)	(0.139)		**(0.011)**	**(0.029)**	**(0.047)**
CMA	0.317	0.168	0.148	CMA	0.212	0.140	0.074
	(0.078)	(0.236)	(0.073)		(0.055)	(0.054)	(0.24)
R-square	0.080	0.646	0.879	R-square	0.109	0.909	0.924

Table 5. Results of relative-strength momentum from the FF5 model regression.

The table reports the results of relative-strength momentum from the Fama-French 5-factor model regression over the sample period of 1.8.2000-1.2.2020. The first column presents the results from the winner-loser momentum portfolios, the second column from the long-only portfolios, and the third column from the short-only portfolios. The results are computed as set out in equation 6 where the dependent variable R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $(R_M - R_f)$ is the risk-adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return, RMW is the difference of returns between stocks with robust profitability and stocks with low profitability, CMA is the difference of returns between stocks of high investment firms and stocks of low investment firms. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

All alphas for the long-only or short-only portfolios are negative and economically insignificant. Statistically significant alphas that can be observed from long strategies (3-3), (9-9), (12-12), and from the short strategy (1-1) are all negative and less than -0.2%. Similarly to the FF3 model in most cases the FF5 factor coefficients are significant at the 5% level. The market factor is again significant both in magnitude and statistically in all cases. Strong co-movement with the market is clearly distinct as the market factor loadings vary from 0.947 to 1.053 in long portfolios and from -1.041 to -0.951 in short portfolios. The explanatory power of the model is much higher for the long and short portfolios than for the winner-loser portfolio as the R-squares vary from 0.646 to 0.926.

Table 6 reports the results of the Fama-French 6-factor model regression set out in equation 7 for the relative-strength ETF momentum strategies over the sample period. Similarly to FF3 and FF5 models the results presented in Table 6 show that the intercepts for all winner-loser portfolios are negative and statistically insignificant except for the (1-1) strategy that yields an average monthly return of -0.6% with p-value 0.045. In general, the FF6 model is able to explain momentum returns better than the FF3 and FF5 models as the R-squares are higher varying from 0.079 to 0.275. The results presented in Tables 4, 5, and 6 clearly emphasize the importance of the momentum factor's capability to explain momentum returns. The UMD coefficient is highly statistically significant for all momentum strategies except for the (1-1) strategy. The factor loadings of the added momentum factor vary between 0.107 and 0.345 showing the positive factor exposure towards stocks that have experienced positive prior returns over the stocks with negative prior returns.

All of the intercepts for each of the long-only and short-only portfolios are also negative from the FF6 model. Statistically significant negative alphas can be observed from the long-only (12-7-1), (9-9) and (12-12) strategies as well as from the (1-1) short only strategy. All statistically significant average monthly returns are less than -0.2%. Momentum factor's importance in explaining the returns is also clearly distinct in the long-only portfolios as the UMD coefficient is significant in seven out of the eight strategies. Momentum factor loadings in long-only portfolios vary from 0.127 to 0.224. In short only portfolios, the UMD coefficient is statistically significant in (7-1-1), (12-1-1), and (6-6) strategies with the factor loading varying between 0.058 and 0.119.

Fama-French 6-Factor (relative-strength momentum)

Strategy:	W-L	Long	Short	**Strategy:**	W-L	Long	Short
7-1-1				**3-3**			
Alpha	-0.003	-0.002	-0.002	Alpha	-0.003	-0.003	-0.001
	(0.101)	(0.066)	(0.096)		(0.089)	(0.009)	(0.265)
Rm - Rf	0.111	**1.054**	**-0.940**	Rm - Rf	-0.012	**1.021**	**-1.029**
	(0.051)	**(0.000)**	**(0.000)**		(0.833)	**(0.000)**	**(0.000)**
SMB	0.105	**0.419**	**-0.313**	SMB	0.094	**0.396**	**-0.305**
	(0.198)	**(0.000)**	**(0.000)**		(0.258)	**(0.000)**	**(0.000)**
HML	0.144	0.051	0.089	HML	0.149	0.053	0.090
	(0.111)	(0.385)	(0.113)		(0.107)	(0.367)	(0.073)
RMW	-0.022	-0.047	0.026	RMW	0.074	0.027	0.042
	(0.849)	(0.526)	(0.715)		(0.506)	(0.701)	(0.486)
CMA	0.106	0.053	0.055	CMA	**0.257**	0.096	**0.162**
	(0.422)	(0.536)	(0.498)		**(0.049)**	(0.251)	**(0.022)**
UMD	**0.280**	**0.189**	**0.090**	UMD	**0.197**	**0.157**	0.041
	(0.000)	**(0.000)**	**(0.002)**		**(0.000)**	**(0.000)**	(0.094)
R-square	0.167	0.869	0.874	R-square	0.203	0.857	0.910
12-1-1				**6-6**			
Alpha	-0.003	-0.002	-0.002	Alpha	-0.002	-0.002	-0.001
	(0.16)	(0.061)	(0.168)		(0.322)	(0.073)	(0.392)
Rm - Rf	**0.204**	**1.121**	**-0.915**	Rm - Rf	0.079	**1.062**	**-0.980**
	(0.000)	**(0.000)**	**(0.000)**		(0.087)	**(0.000)**	**(0.000)**
SMB	0.096	**0.429**	**-0.331**	SMB	**0.249**	**0.489**	**-0.240**
	(0.256)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	0.082	0.014	0.065	HML	**0.163**	0.032	**0.126**
	(0.373)	(0.807)	(0.223)		**(0.027)**	(0.518)	**(0.003)**
RMW	-0.012	-0.028	0.019	RMW	0.172	0.036	**0.135**
	(0.921)	(0.7)	(0.783)		(0.065)	(0.563)	**(0.012)**
CMA	-0.007	0.048	-0.054	CMA	0.120	0.067	0.054
	(0.956)	(0.558)	(0.482)		(0.258)	(0.345)	(0.381)
UMD	**0.345**	**0.224**	**0.119**	UMD	**0.222**	**0.161**	**0.058**
	(0.000)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.009)**
R-square	0.217	0.889	0.886	R-square	0.275	0.905	0.929
12-7-1				**9-9**			
Alpha	-0.002	**-0.002**	-0.001	Alpha	-0.002	**-0.002**	-0.001
	(0.251)	**(0.041)**	(0.456)		(0.19)	**(0.02)**	(0.391)
Rm - Rf	0.096	**1.069**	**-0.971**	Rm - Rf	**0.118**	**1.076**	**-0.955**
	(0.094)	**(0.000)**	**(0.000)**		**(0.011)**	**(0.000)**	**(0.000)**
SMB	**0.186**	**0.486**	**-0.298**	SMB	**0.270**	**0.488**	**-0.217**
	(0.028)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	**-0.181**	-0.094	-0.091	HML	-0.048	-0.038	-0.014
	(0.049)	(0.093)	(0.109)		(0.525)	(0.438)	(0.739)
RMW	0.190	0.020	**0.172**	RMW	0.176	0.050	**0.126**
	(0.108)	(0.783)	**(0.018)**		(0.063)	(0.414)	**(0.018)**
CMA	0.065	0.070	-0.003	CMA	0.058	0.092	-0.033
	(0.625)	(0.386)	(0.968)		(0.593)	(0.191)	(0.592)
UMD	**0.107**	**0.138**	-0.033	UMD	**0.173**	**0.146**	0.025
	(0.026)	**(0.000)**	(0.267)		**(0.000)**	**(0.000)**	(0.265)
R-square	0.079	0.889	0.878	R-square	0.174	0.912	0.923
1-1				**12-12**			
Alpha	**-0.006**	-0.004	**-0.003**	Alpha	-0.003	**-0.003**	-0.001
	(0.045)	(0.078)	**(0.023)**		(0.116)	**(0.009)**	(0.32)
Rm - Rf	-0.114	**0.942**	**-1.052**	Rm - Rf	0.087	**1.075**	**-0.985**
	(0.159)	**(0.000)**	**(0.000)**		(0.057)	**(0.000)**	**(0.000)**
SMB	0.014	**0.350**	**-0.339**	SMB	**0.274**	**0.495**	**-0.220**
	(0.907)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
HML	0.020	0.020	-0.005	HML	-0.138	-0.093	-0.048
	(0.878)	(0.849)	(0.939)		(0.062)	(0.048)	(0.268)

RMW	0.235	0.095	0.132	RMW	0.137	0.051	0.088
	(0.122)	(0.425)	(0.057)		(0.147)	(0.4)	(0.112)
CMA	0.345	0.174	**0.169**	CMA	0.189	0.121	0.070
	(0.057)	(0.223)	**(0.041)**		(0.076)	(0.076)	(0.266)
UMD	-0.074	-0.017	-0.055	UMD	**0.157**	**0.127**	0.028
	(0.235)	(0.726)	(0.053)		**(0.000)**	**(0.000)**	(0.221)
R-square	0.086	0.646	0.881	R-square	0.174	0.919	0.924

Table 6. Results of relative-strength momentum from the FF6 model regression.
The table reports the results of relative-strength momentum from the Fama-French 6-factor model regression for the sample period of 1.8.2000-1.2.2020. The first column presents the results from the winner-loser momentum portfolios, the second column from the long-only portfolios, and the third column from the short-only portfolios. The results are computed as set out in equation 7 where the dependent variable R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $(R_M - R_f)$ is the risk-adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return, RMW is the difference of returns between stocks with robust profitability and stocks with low profitability, CMA is the difference of returns between stocks of high investment firms and stocks of low investment firms, UMD is the difference of returns between two high prior return portfolios and two low prior return portfolios. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

In order to further investigate the performance of the ETF relative-strength momentum strategies, two subsamples are regressed with the Fama-French factor models. Table 7 presents the results of relative-strength strategies over the financial crisis period and the post-crisis period. The financial crisis period is defined to be the period of 1.10.2007-1.3.2009 similar to Tse (2015) and others (Marston 2011; Nofsinger & Varma 2014). Panel A in Table 7 presents the results from the post-crisis period of 1.3.2009-1.2.2020 whereas panel B presents the results from the financial crisis period of 1.10.2007-1.3.2009.

The results reported in Table 7 are similar to the results from the whole sample period. All alphas are insignificant at the 5% level over the post-crisis period. Panel A shows that the (12-1-1) strategy is the only strategy that is able to yield positive alphas from all of the three regression models over the post-crisis period. However, positive alphas are highly insignificant. Statistically significant negative alphas can be observed from the FF5 model with the (12-1-1) and (9-9) strategies over the financial crisis sample period. The abnormal returns for these strategies are -3.7% and -2.1% respectively. The results imply to some extent that momentum strategies are more unprofitable during the crisis that is in contrast with the findings presented in Tse (2015). Comparing significant alphas from the crisis period to the significant alphas observed from the main results show that the alphas during the crisis are much lower than over the whole sample period. Furthermore, the FF6 model has a higher R-square than the FF3 or FF5 models similar to the main results.

Panel A: Post-crisis period				Panel B: Financial crisis period			
Strategy:	FF3	FF5	FF6	**Strategy:**	FF3	FF5	FF6
7-1-1				**7-1-1**			
Alpha	-0.003	-0.003	-0.003	Alpha	-0.002	-0.012	0.002
	(0.308)	(0.315)	(0.289)		(0.85)	(0.279)	(0.853)
Rm - Rf	-0.067	-0.063	-0.002	Rm - Rf	**0.501**	**0.537**	**0.627**
	(0.35)	(0.392)	(0.974)		**(0.002)**	**(0.014)**	**(0.003)**
SMB	0.042	0.001	0.027	SMB	-0.594	-0.509	-0.689
	(0.717)	(0.995)	(0.809)		(0.136)	(0.218)	(0.068)
HML	-0.088	-0.166	0.124	HML	-0.043	0.174	0.252
	(0.393)	(0.245)	(0.406)		(0.803)	(0.431)	(0.197)
RMW		-0.155	-0.099	RMW		0.888	-0.075
		(0.403)	(0.566)			(0.16)	(0.909)
CMA		0.177	-0.031	CMA		-0.741	-0.163
		(0.445)	(0.89)			(0.302)	(0.799)
UMD			**0.270**	UMD			**0.351**
			(0.000)				**(0.041)**
R-square	0.016	0.024	0.157	R-square	0.558	0.638	0.767
12-1-1				**12-1-1**			
Alpha	0.002	0.002	0.002	Alpha	-0.006	**-0.037**	-0.017
	(0.518)	(0.47)	(0.437)		(0.644)	**(0.017)**	(0.192)
Rm - Rf	-0.010	-0.012	0.043	Rm - Rf	**0.482**	**0.554**	**0.678**
	(0.895)	(0.867)	(0.543)		**(0.034)**	**(0.029)**	**(0.003)**
SMB	-0.008	-0.067	-0.043	SMB	-0.500	-0.153	-0.400
	(0.943)	(0.58)	(0.708)		(0.411)	(0.75)	(0.299)
HML	-0.233	-0.283	-0.017	HML	-0.247	0.111	0.219
	(0.027)	(0.051)	(0.911)		(0.368)	(0.672)	(0.295)
RMW		-0.245	-0.194	RMW		**2.390**	1.064
		(0.188)	(0.271)			**(0.006)**	(0.158)
CMA		0.122	-0.068	CMA		**-1.967**	-1.172
		(0.6)	(0.762)			**(0.035)**	(0.115)
UMD			**0.248**	UMD			**0.483**
			(0.000)				**(0.014)**
R-square	0.042	0.057	0.163	R-square	0.302	0.671	0.826
12-7-1				**12-7-1**			
Alpha	-0.002	-0.002	-0.002	Alpha	0.002	-0.011	-0.004
	(0.429)	(0.557)	(0.559)		(0.808)	(0.178)	(0.651)
Rm - Rf	0.129	0.111	0.114	Rm - Rf	**0.310**	0.138	0.180
	(0.067)	(0.125)	(0.123)		**(0.014)**	(0.3)	(0.181)
SMB	0.101	0.074	0.075	SMB	-0.213	-0.092	-0.176
	(0.374)	(0.531)	(0.526)		(0.511)	(0.739)	(0.522)
HML	-0.125	-0.081	-0.066	HML	**-0.980**	**-0.714**	**-0.677**
	(0.218)	(0.563)	(0.672)		**(0.000)**	**(0.000)**	**(0.001)**
RMW		-0.168	-0.166	RMW		0.555	0.106
		(0.352)	(0.364)			(0.199)	(0.838)
CMA		-0.145	-0.156	CMA		**-1.456**	**-1.187**
		(0.523)	(0.505)			**(0.01)**	**(0.036)**
UMD			0.014	UMD			0.164
			(0.834)				(0.192)
R-square	0.049	0.060	0.061	R-square	0.789	0.885	0.904
1-1				**1-1**			
Alpha	-0.003	-0.004	-0.004	Alpha	-0.009	-0.029	-0.023
	(0.496)	(0.389)	(0.387)		(0.593)	(0.192)	(0.399)
Rm - Rf	-0.182	-0.156	-0.183	Rm - Rf	-0.190	-0.152	-0.115
	(0.108)	(0.177)	(0.121)		(0.456)	(0.676)	(0.768)
SMB	-0.066	-0.002	-0.014	SMB	0.430	0.756	0.682

	(0.715)	(0.99)	(0.94)		(0.557)	(0.335)	(0.414)
HML	0.209	0.166	0.037	HML	-0.007	0.053	0.085
	(0.199)	(0.459)	(0.882)		(0.983)	(0.9)	(0.848)
RMW		0.348	0.323	RMW		1.538	1.142
		(0.232)	(0.267)			(0.202)	(0.472)
CMA		0.135	0.228	CMA		-1.181	-0.944
		(0.71)	(0.541)			(0.388)	(0.54)
UMD			-0.120	UMD			0.144
			(0.245)				(0.693)
R-square	0.033	0.046	0.056	R-square	0.054	0.215	0.227
3-3				**3-3**			
Alpha	-0.001	-0.001	-0.001	Alpha	-0.012	-0.029	-0.009
	(0.75)	(0.638)	(0.635)		(0.283)	(0.052)	(0.476)
Rm - Rf	**-0.154**	-0.138	-0.097	Rm - Rf	0.137	0.053	0.175
	(0.026)	(0.053)	(0.169)		(0.423)	(0.816)	(0.355)
SMB	0.005	0.003	0.021	SMB	-0.093	0.077	-0.166
	(0.966)	(0.98)	(0.853)		(0.848)	(0.874)	(0.673)
HML	0.014	-0.063	0.134	HML	-0.132	0.109	0.214
	(0.887)	(0.644)	(0.368)		(0.549)	(0.683)	(0.324)
RMW		0.060	0.098	RMW		1.072	-0.229
		(0.735)	(0.571)			(0.163)	(0.76)
CMA		0.195	0.053	CMA		-1.496	-0.716
		(0.384)	(0.81)			(0.099)	(0.336)
UMD			**0.184**	UMD			**0.475**
			(0.003)				**(0.019)**
R-square	0.044	0.051	0.116	R-square	0.059	0.306	0.612
6-6				**6-6**			
Alpha	-0.001	-0.001	-0.001	Alpha	0.001	-0.019	-0.009
	(0.675)	(0.773)	(0.776)		(0.89)	(0.053)	(0.386)
Rm - Rf	0.015	0.007	0.029	Rm - Rf	**0.324**	0.245	**0.312**
	(0.78)	(0.907)	(0.613)		**(0.035)**	(0.131)	**(0.046)**
SMB	0.076	0.053	0.062	SMB	-0.221	0.006	-0.126
	(0.394)	(0.567)	(0.495)		(0.588)	(0.984)	(0.672)
HML	-0.108	-0.109	-0.003	HML	-0.102	0.188	0.246
	(0.175)	(0.321)	(0.979)		(0.578)	(0.303)	(0.148)
RMW		-0.126	-0.106	RMW		**1.332**	0.622
		(0.374)	(0.451)			**(0.018)**	(0.286)
CMA		-0.024	-0.100	CMA		**-1.714**	**-1.288**
		(0.891)	(0.578)			**(0.011)**	**(0.037)**
UMD			**0.099**	UMD			0.259
			(0.049)				(0.071)
R-square	0.020	0.026	0.056	R-square	0.311	0.669	0.765
9-9				**9-9**			
Alpha	-0.001	-0.001	-0.001	Alpha	-0.002	**-0.021**	-0.009
	(0.625)	(0.74)	(0.743)		(0.848)	**(0.048)**	(0.386)
Rm - Rf	0.080	0.070	0.079	Rm - Rf	**0.348**	0.260	**0.338**
	(0.158)	(0.233)	(0.186)		**(0.029)**	(0.14)	**(0.041)**
SMB	0.072	0.048	0.052	SMB	-0.410	-0.207	-0.362
	(0.433)	(0.611)	(0.583)		(0.336)	(0.562)	(0.263)
HML	-0.154	-0.123	-0.078	HML	**-0.541**	-0.211	-0.144
	(0.06)	(0.279)	(0.535)		**(0.011)**	(0.288)	(0.403)
RMW		-0.106	-0.097	RMW		1.268	0.441
		(0.47)	(0.508)			(0.034)	(0.467)
CMA		-0.100	-0.132	CMA		**-1.719**	-1.223
		(0.586)	(0.484)			**(0.016)**	(0.056)
UMD			0.041	UMD			**0.302**
			(0.427)				**(0.05)**
R-square	0.045	0.052	0.057	R-square	0.462	0.711	0.807
12-12				**12-12**			
Alpha	-0.001	-0.001	-0.001	Alpha	-0.004	-0.008	-0.011
	(0.539)	(0.635)	(0.634)		(0.649)	(0.471)	(0.433)
Rm - Rf	0.057	0.053	0.075	Rm - Rf	**0.275**	0.265	0.246
	(0.239)	(0.289)	(0.134)		**(0.038)**	(0.175)	(0.237)
SMB	0.060	0.010	0.020	SMB	-0.414	-0.405	-0.368
	(0.443)	(0.901)	(0.805)		(0.251)	(0.318)	(0.395)
HML	**-0.211**	**-0.225**	-0.119	HML	**-0.670**	**-0.523**	**-0.539**
	(0.003)	**(0.022)**	(0.265)		**(0.001)**	**(0.031)**	**(0.037)**
RMW		-0.174	-0.154	RMW		0.330	0.531

		(0.167)	(0.215)			(0.584)	(0.517)
CMA		0.019	-0.057	CMA		-0.432	-0.552
		(0.902)	(0.719)			(0.538)	(0.489)
UMD			**0.099**	UMD			-0.073
			(0.025)				(0.699)
R-square	0.074	0.086	0.122	R-square	0.613	0.632	0.638

Table 7. Subsample results of relative-strength strategies.
The table reports the subsample results of relative-strength momentum from the FF3, FF5, and FF6 model regression for the financial crisis period of 1.10.2007-1.3.2009 and post-crisis period of 1.3.2009-1.2.2020. Panel A presents the results from the post-crisis period and panel B from the financial crisis period. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

The results from the FF3, FF5, and FF6 regression models clearly show that the null hypothesis holds and cannot be rejected for the relative-strength smart beta ETF momentum strategies. The alphas of the momentum strategies computed from the regression models are all negative and statistically insignificant at the 5% significance level. The only statistically significant alphas can be observed with the (1-1) strategy from FF5 and FF6 models but the average monthly return is however negative -0.6%. Thus, the results strongly show that investors are not able to achieve positive abnormal returns over the sample period by implementing relative-strength momentum strategies in smart beta ETFs. The results remain the same with long-only and short-only portfolios and with the subsamples of the financial crisis and post-crisis periods.

The economic performance of the smart beta ETF relative-strength momentum strategies presented in this thesis is weaker than the performance documented in previous studies of sector ETF momentum, see (Andreu et al. 2013; Du et al. 2014; Tse 2015). Similarly to Andreu et al. (2013), Du et al. (2014), and Tse (2015) the momentum returns are statistically insignificant when adjusted with the Fama-French factor models. Moreover, the results presented in this thesis are in sharp contrast with the factor momentum results documented by Arnott et al. (2019). For instance, Arnott et al. (2019) report a significant abnormal monthly average return of 0.89% with a t-value of 4.37 after adjusted with the FF6 model for a momentum strategy that rotates the five factors of the FF5 model.

6.2 Time-series momentum

Table 8 reports the average monthly excess returns, standard deviations, and Sharpe ratios of the eight different time-series momentum strategies implemented in smart beta ETFs. In addition to winner-loser portfolios, Table 8 also reports the statistics from long-only portfolios and short-only portfolios in order to have further implications about the drivers of the momentum strategies. The statistics and returns of a simple buy-and-hold strategy are also presented in Table 8 for comparison.

Table 8 shows that all of the winner-loser portfolios except the (9-9) and (12-12) strategies are yielding positive average returns over the sample period. The average returns vary from -0.09% to 0.648% where the highest return is observed from the (12-1-1) strategy and the lowest return from the (9-9) and (12-12) strategies. Table 8 clearly implies that the time-series momentum strategies are outperforming the relative-strength strategies reported in the previous chapter. However, only the Novy-Marx (2012) based strategies (12-1-1) and (12-7-1) are able to achieve excess returns over the buy-and-hold strategy. These two strategies are also outperforming the buy-and-hold strategy in terms of Sharpe ratios. The average monthly returns of the (12-1-1) and (12-7-1) strategies are 0.648% and 0.530% respectively with Sharpe ratios of 0.159 and 0.131 respectively while the average return of the buy-and-hold strategy is 0.457% with Sharpe ratio of 0.097. The lowest Sharpe ratio of -0.040 is observed from the (12-12) strategy. Standard deviations of the momentum strategies vary between 2.3% and 4.1% where the (12-12) strategy has the lowest standard deviation and the (12-1-1) strategy the highest.

Similarly to the relative-strength strategies the weak performance of time-series momentum strategies is driven by the poor performance of the short portfolios over the sample period. All of the short portfolios yield negative average monthly excess returns varying from -0.650% to -0.065% where the (12-12) strategy yields the lowest return and the (12-1-1) the highest return. Table 8 shows that the short portfolios actually yield similar positive returns than the long portfolios over the sample period except for the

(12-1-1) and (12-7-1) strategies that are consequently the best performing winner-loser portfolios.

Time series momentum

Strategy: K-(S)-H	W-L Portfolio	Long Portfolio	Short Portfolio
7-1-1			
Mean %	0.067	0.259	-0.309
Standard deviation %	3.761	4.120	4.336
Sharpe ratio	0.018	0.063	-0.071
12-1-1			
Mean %	0.648	0.603	-0.065
Standard deviation %	4.087	3.805	3.832
Sharpe ratio	0.159	0.159	-0.017
12-7-1			
Mean %	0.530	0.654	-0.234
Standard deviation %	4.039	3.815	3.849
Sharpe ratio	0.131	0.171	-0.061
1-1			
Mean %	0.004	0.396	-0.519
Standard deviation %	3.915	3.736	4.287
Sharpe ratio	0.001	0.106	-0.121
3-3			
Mean %	0.142	0.349	-0.331
Standard deviation %	3.122	4.233	4.690
Sharpe ratio	0.045	0.082	-0.071
6-6			
Mean %	0.033	0.507	-0.592
Standard deviation %	2.421	4.559	4.741
Sharpe ratio	0.014	0.111	-0.125
9-9			
Mean %	-0.090	0.406	-0.610
Standard deviation %	2.444	4.446	4.619
Sharpe ratio	-0.037	0.091	-0.132
12-12			
Mean %	-0.090	0.449	-0.650
Standard deviation %	2.267	4.532	4.600
Sharpe ratio	-0.040	0.099	-0.141
Buy-and-hold			
Mean %	0.457		
Standard deviation %	4.704		
Sharpe ratio	0.097		

Table 8. Returns and descriptive statistics of time-series momentum.
The table reports the average monthly excess returns, standard deviations, and Sharpe ratios of time-series momentum strategies over the whole sample period 1.8.2000-1.2.2020. Strategies are denoted by K-(S)-H where K is the ranking period, S is the months skipped between the ranking and holding periods, and H is the holding period. The first column reports the results

from winner-loser portfolios, the second column from long-only portfolios, and the third from short-only portfolios. The results from the short portfolio are presented in terms of the short position in the underlying ETFs in the portfolio. The excess returns are computed with the 1-month Treasury bill rate retrieved from Kenneth R. French Data Library (2020) provided by Ibbotson Associates (French 2020).

All of the long portfolios yield positive returns where the (12-7-1) strategy is the most profitable with a return of 0.654% and the (7-1-1) strategy the most unprofitable with the lowest return of 0.259%. The highest Sharpe ratio in short portfolios is observed from the strategy the (12-1-1) strategy with the Sharpe ratio of -0.017 and in long portfolios from the (12-7-1) strategy with a Sharpe ratio of 0.171. The lowest Sharpe ratio in short portfolios is -0.141 with the (7-1-1) strategy. In long portfolios, the lowest Sharpe ratio is 0.063 with the (7-1-1) strategy. The standard deviations of short portfolios vary between 3.8% and 4.7% while the standard deviations of long portfolios vary between 3.7% and 4.6%.

The monthly average excess returns of time-series momentum strategies reported in Table 8 are consistent in terms of economic significance with the results of time-series sector ETF momentum presented in Tse (2015). The monthly average returns reported in Tse (2015) for K=H strategies are varying from 0.156% to 0.406%. The most profitable strategy (12-1-1) presented in Table 8 yields a slightly higher average return than the most profitable strategy reported in Tse (2015). For instance, the most profitable strategy (12-1-1) provides a monthly return of 0.648% compared to the return of 0.551% from the most profitable sector ETF strategy documented in Tse (2015).

Table 9 reports the results of the Fama-French 3-factor model regression set out in equation 5 for the time-series ETF momentum strategies over the sample period. All of the alphas presented in Table 9 are positive except the alphas of the longer holding period strategies (9-9) and (12-12). However, only the (12-1-1) strategy is statistically significant at the 5% significance level and the (12-7-1) at the 10% significance level. The monthly average abnormal return from the (12-1-1) strategy is 0.618% and from the (12-7-1) strategy 0.488% with the p-values of 0.025 and 0.074 respectively. The FF3 model is not able to explain the excess returns of the (12-1-1) strategy at the acceptable 5% significance level and the excess returns of the (12-7-1) at the 10% significance level. Thus, the results suggest that these strategies are able to generate significant abnormal returns over the sample period. In general, the three factors of the model are not sufficient to explain the excess returns of the momentum strategies as in most cases the p-values of the factor coefficients are above the 5% significance level. However, the size factor is able to capture the excess returns at the 5% significance level in the most profitable strategy (12-1-1) with the factor loading of 0.280. This implies to some degree that the excess returns of the (12-1-1) strategy can be explained by the returns of small firms. Nevertheless, the explanatory power of the model is rather weak across all strategies as the R-squares vary from 0.008 to 0.056.

Fama-French 3-Factor (time-series momentum)

Strategy:	W-L	Long	Short	**Strategy:**	W-L	Long	Short
7-1-1				**3-3**			
Alpha	0.001	-0.002	0.001	Alpha	0.002	-0.001	0.001
	(0.816)	(0.163)	(0.384)		(0.409)	(0.627)	(0.439)
Rm - Rf	-0.087	**0.713**	**-0.796**	Rm - Rf	**-0.139**	**0.777**	**-0.911**
	(0.149)	**(0.000)**	**(0.000)**		**(0.005)**	**(0.000)**	**(0.000)**
SMB	**0.231**	**0.393**	**-0.163**	SMB	0.070	**0.312**	**-0.243**
	(0.025)	**(0.000)**	**(0.018)**		(0.408)	**(0.000)**	**(0.000)**
HML	0.172	0.002	**0.167**	HML	**0.158**	0.075	0.075
	(0.052)	(0.968)	**(0.005)**		**(0.02)**	(0.105)	(0.109)
R-square	0.041	0.718	0.676	R-square	0.056	0.766	0.800
12-1-1				**6-6**			
Alpha	**0.006**	0.002	0.003	Alpha	0.000	-0.001	0.000
	(0.025)	(0.256)	(0.048)		(0.852)	(0.481)	(0.85)
Rm - Rf	-0.033	**0.642**	**-0.672**	Rm - Rf	-0.017	**0.935**	**-0.948**
	(0.629)	**(0.000)**	**(0.000)**		(0.655)	**(0.000)**	**(0.000)**
SMB	**0.280**	**0.365**	-0.083	SMB	0.010	**0.310**	**-0.302**
	(0.016)	**(0.000)**	(0.246)		(0.883)	**(0.000)**	**(0.000)**
HML	-0.122	-0.087	-0.037	HML	**0.195**	**0.113**	0.078
	(0.249)	(0.135)	(0.568)		**(0.001)**	**(0.001)**	(0.083)
R-square	0.031	0.660	0.584	R-square	0.052	0.905	0.839
12-7-1				**9-9**			
Alpha	0.005	0.002	0.002	Alpha	-0.001	-0.002	0.000
	(0.074)	(0.142)	(0.34)		(0.579)	(0.101)	(0.787)
Rm - Rf	0.023	**0.683**	**-0.657**	Rm - Rf	-0.019	**0.911**	**-0.927**
	(0.732)	**(0.000)**	**(0.000)**		(0.646)	**(0.000)**	**(0.000)**
SMB	0.150	**0.277**	-0.124	SMB	0.055	**0.318**	**-0.262**
	(0.194)	**(0.000)**	(0.085)		(0.423)	**(0.000)**	**(0.000)**
HML	-0.119	-0.035	-0.086	HML	-0.063	-0.043	-0.023
	(0.259)	(0.531)	(0.188)		(0.31)	(0.271)	(0.647)
R-square	0.015	0.684	0.580	R-square	0.008	0.879	0.823
1-1				**12-12**			
Alpha	0.001	0.001	-0.001	Alpha	-0.001	-0.002	-0.001
	(0.739)	(0.62)	(0.417)		(0.441)	(0.084)	(0.548)
Rm - Rf	**-0.192**	**0.615**	**-0.802**	Rm - Rf	0.014	**0.947**	**-0.930**
	(0.002)	**(0.000)**	**(0.000)**		(0.711)	**(0.000)**	**(0.000)**
SMB	0.020	**0.181**	**-0.160**	SMB	0.090	**0.356**	**-0.264**
	(0.847)	**(0.007)**	**(0.011)**		(0.157)	**(0.000)**	**(0.000)**
HML	0.022	0.019	-0.006	HML	-0.070	-0.021	-0.052
	(0.798)	(0.728)	(0.903)		(0.233)	(0.541)	(0.294)

R-square	0.044	0.582	0.719	R-square	0.017	0.918	0.832

Table 9. Results of time-series momentum from the FF3 model regression.
The table reports the results of time-series momentum from the Fama-French 3-factor model regression over the sample period of 1.8.2000-1.2.2020. The first column presents the results from the winner-loser momentum portfolios, the second column from the long-only portfolios, and the third column from the short-only portfolios. The results are computed as set out in equation 5 where the dependent variable R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $\left(R_M - R_f\right)$ is the risk-adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

None of the only long or short portfolios presented in Table 9 are able to generate statistically significant alphas. Only three out of the eight long-only portfolios have positive alphas that are all less than 0.2% while four short only portfolios have alphas larger than zero but less than 0.3%. The FF3 model's capability to explain long and short portfolios is better than in winner-loser portfolios. In most cases, the factor coefficients are significant at the 5% level. For instance, the market factor is significant in all cases with the factor loading varying from 0.615 to 0.947 in long portfolios and from -0.948 to -0.657 in short portfolios implying that the returns of long and short portfolios strongly co-move with the market. This is consistent with the discussed results of the relative-strength strategies and that the ETFs used in the sample comprises a large part of the total market capitalization in the U.S. market. The exposure to the market factor seems to increase when moving from shorter holding period strategies to the longer holding period strategies. The explanatory power of the model is also much higher for the long-only and short-only portfolios than for the winner-loser portfolios as the R-squares vary from 0.580 to 0.918.

Table 10 reports the results of the Fama-French 5-factor model regression set out in equation 6 for the time-series ETF momentum strategies over the sample period. Table 10 shows that the intercepts across all winner-loser portfolios are statistically insignificant at the 5% significance level. The significant abnormal return of the (12-1-1) strategy from the FF3 regression can be captured by the FF5 model as the p-value of the intercept for the (12-1-1) strategy is 0.379. The addition of the profitability and investment factors increases the FF5 model's capability to explain momentum returns.

For instance, in the (12-1-1) strategy the RMW and CMA factor coefficients are both significant with the factor loadings of 0.650 and 0.439 respectively. In fact, the excess returns of the (12-1-1) strategy are captured by all of the FF5 factors except the market factor. In general, the FF5 model is more sufficient than the FF3 model in explaining the excess momentum returns as the R-squares are higher for the FF5 model.

Fama-French 5-Factor (time-series momentum)

Strategy:	W-L	Long	Short	**Strategy:**	W-L	Long	Short
7-1-1				**3-3**			
Alpha	-0.003	**-0.003**	-0.001	Alpha	0.000	-0.001	0.000
	(0.237)	**(0.028)**	(0.654)		(0.951)	(0.351)	(0.854)
Rm - Rf	0.087	**0.776**	**-0.684**	Rm - Rf	-0.065	**0.805**	**-0.867**
	(0.197)	**(0.000)**	**(0.000)**		(0.26)	**(0.000)**	**(0.000)**
SMB	**0.303**	**0.421**	-0.120	SMB	0.087	**0.325**	**-0.240**
	(0.003)	**(0.000)**	(0.071)		(0.308)	**(0.000)**	**(0.000)**
HML	-0.184	**-0.139**	-0.049	HML	-0.005	-0.027	0.016
	(0.092)	**(0.04)**	(0.494)		(0.956)	(0.673)	(0.804)
RMW	**0.500**	**0.218**	**0.282**	RMW	0.175	0.081	0.087
	(0.000)	**(0.01)**	**(0.002)**		(0.106)	(0.27)	(0.243)
CMA	**0.576**	0.090	**0.490**	CMA	0.251	0.059	**0.191**
	(0.000)	(0.356)	**(0.000)**		(0.057)	(0.513)	**(0.037)**
R-square	0.143	0.725	0.715	R-square	0.082	0.767	0.807
12-1-1				**6-6**			
Alpha	0.002	0.000	0.001	Alpha	-0.001	-0.002	-0.001
	(0.379)	(0.955)	(0.413)		(0.423)	(0.095)	(0.509)
Rm - Rf	0.143	**0.724**	**-0.578**	Rm - Rf	0.063	**0.978**	**-0.911**
	(0.06)	**(0.000)**	**(0.000)**		(0.158)	**(0.000)**	**(0.000)**
SMB	**0.374**	**0.435**	-0.059	SMB	0.033	**0.329**	**-0.298**
	(0.001)	**(0.000)**	(0.403)		(0.615)	**(0.000)**	**(0.000)**
HML	**-0.397**	**-0.203**	-0.197	HML	0.027	-0.025	0.047
	(0.001)	**(0.003)**	(0.009)		(0.701)	(0.558)	(0.418)
RMW	**0.650**	**0.372**	**0.278**	RMW	**0.206**	**0.120**	0.085
	(0.000)	**(0.000)**	**(0.003)**		**(0.02)**	**(0.024)**	(0.242)
CMA	**0.439**	0.023	**0.417**	CMA	**0.321**	**0.152**	**0.172**
	(0.017)	(0.822)	**(0.000)**		**(0.002)**	**(0.014)**	**(0.041)**
R-square	0.121	0.688	0.621	R-square	0.112	0.909	0.844
12-7-1				**9-9**			
Alpha	0.001	0.000	0.000	Alpha	-0.002	**-0.003**	-0.001
	(0.645)	(0.862)	(0.95)		(0.153)	**(0.017)**	(0.475)
Rm - Rf	**0.191**	**0.768**	**-0.574**	Rm - Rf	0.053	**0.950**	**-0.894**
	(0.012)	**(0.000)**	**(0.000)**		(0.251)	**(0.000)**	**(0.000)**
SMB	**0.253**	**0.347**	-0.092	SMB	0.079	**0.330**	**-0.250**
	(0.029)	**(0.000)**	(0.208)		(0.253)	**(0.000)**	**(0.000)**
HML	**-0.368**	**-0.172**	**-0.199**	HML	**-0.203**	**-0.171**	-0.035
	(0.003)	**(0.008)**	**(0.01)**		**(0.007)**	**(0.000)**	(0.564)
RMW	**0.624**	**0.353**	**0.270**	RMW	**0.214**	0.114	0.099
	(0.000)	**(0.000)**	**(0.005)**		**(0.023)**	(0.058)	(0.193)
CMA	**0.425**	0.133	**0.293**	CMA	**0.295**	**0.177**	0.119
	(0.02)	(0.172)	**(0.012)**		**(0.009)**	**(0.014)**	(0.19)
R-square	0.102	0.713	0.605	R-square	0.056	0.884	0.826
1-1				**12-12**			
Alpha	0.000	0.000	-0.001	Alpha	-0.002	**-0.002**	-0.001
	(0.975)	(0.909)	(0.4)		(0.128)	**(0.016)**	(0.325)
Rm - Rf	**-0.157**	**0.638**	**-0.793**	Rm - Rf	0.070	**0.973**	**-0.900**
	(0.031)	**(0.000)**	**(0.000)**		(0.109)	**(0.000)**	**(0.000)**
SMB	0.020	**0.188**	**-0.169**	SMB	0.108	**0.381**	**-0.272**
	(0.857)	**(0.006)**	**(0.009)**		(0.095)	**(0.000)**	**(0.000)**
HML	-0.119	-0.110	-0.016	HML	**-0.196**	**-0.112**	-0.088
	(0.309)	(0.135)	(0.823)		**(0.005)**	**(0.006)**	(0.136)
RMW	0.017	0.014	-0.004	RMW	0.164	**0.114**	0.049

	(0.903)	(0.871)	(0.963)		(0.061)	**(0.024)**	(0.507)
CMA	0.309	**0.213**	0.094	CMA	**0.274**	0.059	**0.217**
	(0.065)	**(0.043)**	(0.344)		**(0.009)**	(0.332)	**(0.014)**
R-square	0.058	0.590	0.721	R-square	0.059	0.921	0.837

Table 10. Results of time-series momentum from the FF5 model regression.

The table reports the results of time-series momentum from the Fama-French 5-factor model regression over the sample period of 1.8.2000-1.2.2020. The first column presents the results from the winner-loser momentum portfolios, the second column from the long-only portfolios, and the third column from the short-only portfolios. The results are computed as set out in equation 6 where the dependent variable R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $(R_M - R_f)$ is the risk adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return, RMW is the difference of returns between stocks with robust profitability and stocks with low profitability, CMA is the difference of returns between stocks of high investment firms and stocks of low investment firms. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

Table 10 shows that the alphas of the long and short portfolios are statistically insignificant except for the long (7-1-1), (9-9), and (12-12) portfolios. However, significant alphas are all negative and less than -0.2%. Similarly to the FF3 model, the FF5 factor coefficients are in most cases significant at the 5% level. The market factor is again significant both in magnitude and statistically in all cases. Strong co-movement with the market is distinct as the market factor loadings vary from 0.638 to 0.978 in long portfolios and from -0.911 to -0.574 in short portfolios. The explanatory power of the model is much higher for the long and short portfolios than for the winner-loser portfolio as the R-squares vary from 0.590 to 0.921.

Moving to Table 11 that reports the results of the Fama-French 6-factor model regression set out in equation 7 for the time-series ETF momentum strategies over the sample period. Similarly to the results of the FF5 model, the results presented in Table 11 show that the intercepts across all winner-loser portfolios are statistically insignificant and not different from zero. The monthly average abnormal returns vary from -0.3% to 0.2% but are nevertheless insignificant at the acceptable 5% significance level. In general, the FF6 model is able to explain momentum returns better than the FF3 and FF5 models as the R-squares are higher varying from 0.142 to 0.384 except for the (1-1) strategy where the R-square is only 0.066. The results reported from FF3, FF5, and FF6 model regressions clearly emphasize the importance of the momentum factor in the factor model. Similarly to the results of the relative-strength momentum, the UMD coefficient is highly significant for all momentum strategies except for the (1-1) strategy. The significant factor loadings of the added momentum factor vary between 0.176 and 0.496 showing the positive factor exposure towards stocks that have experienced positive prior returns over the stocks with negative prior returns.

Three significant intercepts can be observed from the long-only portfolios. However, the significant abnormal returns from the long (7-1-1), (9-9), and (12-12) portfolios are all negative and less than -0.2%. The intercepts for the other long and short portfolios are all insignificant at 5% significance level. Momentum factor's importance in explaining the returns is also clearly distinct in the long-only portfolios as the UMD coefficient is significant in six out of the eight long portfolios presented in Table 11. Significant momentum factor loadings in long-only portfolios vary from 0.087 to 0.226. In short only portfolios, the UMD coefficient is statistically significant across all strategies except for the (12-7-1) strategy. In short strategies, the momentum factor loading varies between 0.087 and 0.277. Similar to the results of the FF3 and FF5 models, the R-square of the FF6 model remains high for the long and short portfolios as the highest R-square is 0.937 and the lowest 0.590.

Fama-French 6-Factor (time-series momentum)

Strategy:	W-L	Long	Short	**Strategy:**	W-L	Long	Short
7-1-1				**3-3**			
Alpha	-0.003	**-0.003**	-0.001	Alpha	0.000	-0.001	0.000
	(0.214)	**(0.019)**	(0.682)		(0.93)	(0.338)	(0.845)
Rm - Rf	**0.200**	**0.840**	**-0.636**	Rm - Rf	0.002	**0.853**	**-0.847**
	(0.001)	**(0.000)**	**(0.000)**		(0.969)	**(0.000)**	**(0.000)**
SMB	**0.273**	**0.404**	-0.133	SMB	0.070	**0.313**	**-0.246**
	(0.002)	**(0.000)**	(0.037)		(0.39)	**(0.000)**	**(0.000)**
HML	-0.009	-0.039	0.026	HML	0.093	0.042	0.046
	(0.93)	(0.533)	(0.714)		(0.305)	(0.493)	(0.483)
RMW	0.181	0.035	0.145	RMW	0.051	-0.006	0.049
	(0.147)	**(0.655)**	(0.107)		(0.631)	(0.935)	(0.517)
CMA	**0.393**	**-0.014**	**0.412**	CMA	0.170	0.002	0.166
	(0.006)	(0.872)	**(0.000)**		(0.179)	(0.983)	(0.069)
UMD	**0.395**	**0.226**	**0.170**	UMD	**0.215**	**0.151**	**0.065**
	(0.000)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.038)**
R-square	0.338	0.778	0.743	R-square	0.171	0.791	0.810
12-1-1				**6-6**			
Alpha	0.002	0.000	0.001	Alpha	-0.001	-0.002	-0.001
	(0.397)	(0.849)	(0.442)		(0.384)	(0.057)	(0.519)
Rm - Rf	**0.292**	**0.789**	**-0.495**	Rm - Rf	**0.147**	**1.028**	**-0.877**
	(0.000)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**

SMB	**0.299**	**0.402**	-0.101	SMB	0.008	**0.314**	**-0.308**
	(0.003)	**(0.000)**	(0.11)		(0.879)	**(0.000)**	**(0.000)**
HML	-0.157	-0.098	-0.063	HML	**0.158**	0.053	0.100
	(0.148)	(0.127)	(0.358)		**(0.01)**	(0.149)	(0.085)
RMW	**0.313**	**0.225**	0.089	RMW	-0.038	-0.026	-0.013
	(0.023)	**(0.006)**	(0.304)		(0.621)	(0.579)	(0.857)
CMA	**0.364**	-0.010	0.375	CMA	**0.173**	0.063	0.113
	(0.021)	(0.913)	(0.000)		**(0.047)**	(0.228)	(0.171)
UMD	**0.496**	**0.217**	**0.277**	UMD	**0.300**	**0.180**	**0.120**
	(0.000)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
R-square	0.352	0.738	0.703	R-square	0.384	0.937	0.856
12-7-1				**9-9**			
Alpha	0.001	0.000	0.000	Alpha	-0.003	**-0.003**	-0.001
	(0.684)	(0.884)	(0.888)		(0.063)	**(0.003)**	(0.415)
Rm - Rf	**0.252**	**0.782**	**-0.528**	Rm - Rf	**0.153**	**1.011**	**-0.855**
	(0.001)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.000)**
SMB	**0.222**	**0.339**	-0.115	SMB	0.030	**0.300**	**-0.269**
	(0.05)	**(0.000)**	(0.105)		(0.609)	**(0.000)**	**(0.000)**
HML	**-0.269**	**-0.149**	-0.124	HML	-0.061	**-0.085**	0.020
	(0.029)	**(0.027)**	(0.107)		(0.355)	**(0.047)**	(0.745)
RMW	**0.484**	**0.321**	0.165	RMW	-0.002	-0.018	0.016
	(0.002)	**(0.000)**	(0.091)		(0.978)	(0.742)	(0.835)
CMA	**0.394**	0.126	0.269	CMA	**0.230**	**0.138**	0.095
	(0.028)	(0.196)	(0.017)		**(0.017)**	**(0.027)**	(0.286)
UMD	**0.204**	0.048	0.154	UMD	**0.315**	**0.192**	**0.121**
	(0.002)	(0.171)	(0.000)		**(0.000)**	**(0.000)**	**(0.000)**
R-square	0.142	0.715	0.630	R-square	0.316	0.913	0.836
1-1				**12-12**			
Alpha	0.000	0.000	-0.001	Alpha	-0.003	**-0.002**	-0.001
	(0.971)	(0.91)	(0.399)		(0.092)	**(0.01)**	(0.295)
Rm - Rf	**-0.181**	**0.641**	**-0.819**	Rm - Rf	**0.122**	**0.999**	**-0.875**
	(0.016)	**(0.000)**	**(0.000)**		**(0.005)**	**(0.000)**	**(0.000)**
SMB	0.024	**0.187**	**-0.164**	SMB	0.085	**0.369**	**-0.283**
	(0.822)	**(0.007)**	**(0.011)**		(0.169)	**(0.000)**	**(0.000)**
HML	-0.157	-0.106	-0.057	HML	-0.112	-0.070	-0.046
	(0.192)	(0.162)	(0.424)		(0.103)	(0.084)	(0.441)
RMW	0.060	0.009	0.044	RMW	0.046	**0.056**	-0.009
	(0.665)	(0.916)	(0.591)		(0.593)	**(0.27)**	(0.9)
CMA	**0.342**	**0.210**	0.130	CMA	**0.245**	0.044	**0.203**
	(0.043)	**(0.049)**	(0.192)		**(0.014)**	(0.446)	**(0.02)**
UMD	-0.080	0.008	**-0.087**	UMD	**0.176**	**0.087**	**0.087**
	(0.166)	(0.815)	**(0.01)**		**(0.000)**	**(0.000)**	**(0.006)**
R-square	0.066	0.590	0.729	R-square	0.152	0.927	0.843

Table 11. Results of time-series momentum from the FF6 model regression.

The table reports the results of time-series momentum from the Fama-French 6-factor model regression over the sample period of 1.8.2000-1.2.2020. The first column presents the results from the winner-loser momentum portfolios, the second column from the long-only portfolios, and the third column from the short-only portfolios. The results are computed as set out in equation 7 where the dependent variable R_{mom} is the excess return of ETF momentum strategies, α is the intercept, $(R_M - R_f)$ is the risk-adjusted market return, SMB is the difference between small stocks returns and the large stocks returns, HML is the difference between high book-to-market stocks return and the low book-to-market stocks return, RMW is the difference of returns between stocks with robust profitability and stocks with low profitability, CMA is the difference of returns between stocks of high investment firms and stocks of low investment firms, UMD is the difference of returns between two high prior return portfolios and two low prior return portfolios. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

Tse (2015) shows that the better performance of time-series momentum strategies over the buy-and-hold strategy is mainly due to the high performance realized during the financial crisis period of 2009-2014. During the post-crisis period, Tse (2015) proves that the momentum strategy is not able to outperform the buy-and-hold strategy. Similar finding that sector ETF momentum profits are driven by the financial crisis period can be also interpreted from the results documented by Andreu et al. (2013).

Figure 2 draws the cumulative excess returns of the (12-1-1) time-series smart beta ETF momentum strategy and the buy-and-hold strategy from 1.6.2001 to 1.2.2020. The cumulative return for the time-series momentum strategy is 254% and for the buy-and-hold 147% over the sample period. The momentum strategy is also outperforming the buy-and-hold strategy measured by Sharpe ratios. The Sharpe ratio for the (12-1-1) momentum strategy is 0.159 and for the buy-and-hold strategy 0.111 over the sample period. The higher cumulative returns of the momentum strategy during the financial crisis period is clearly visible in Figure 2. Furthermore, Figure 2 is almost identical to Figure 2 presented in Tse (2015) that shows the cumulative excess returns of sector ETF time-series momentum and buy-and-hold strategies over the period of 2000-2014.

During the post-crisis period of 1.3.2009-1.2.2020, the buy-and-hold strategy is outperforming the momentum strategy similarly as reported in Tse (2015). The financial crisis-period is defined to be the period of 1.10.2007-1.3.2009 similar to Tse (2015) and others (Marston 2011; Nofsinger & Varma 2014). The cumulative excess return of the buy-and-hold during the post-crisis period is 284% while the momentum strategy offers a cumulative excess return of only 62%. Buy-and-hold is outperforming the momentum strategy also in terms of Sharpe ratios as the post-crisis Sharpe ratios are 0.27 and 0.12 respectively. The outperformance of the buy-and-hold over the momentum strategy remains the same also when the financial crisis period is omitted from the sample. The results are consistent with the findings of Moskowitz et al. (2012) that time-series momentum performs best during extreme markets and with the findings of Andreu et al. (2013) and Tse (2015) in sector ETFs. Furthermore, these results extend the findings of Tse (2015) to smart beta ETFs and imply that the results remain the same with a longer post-crisis sample period.

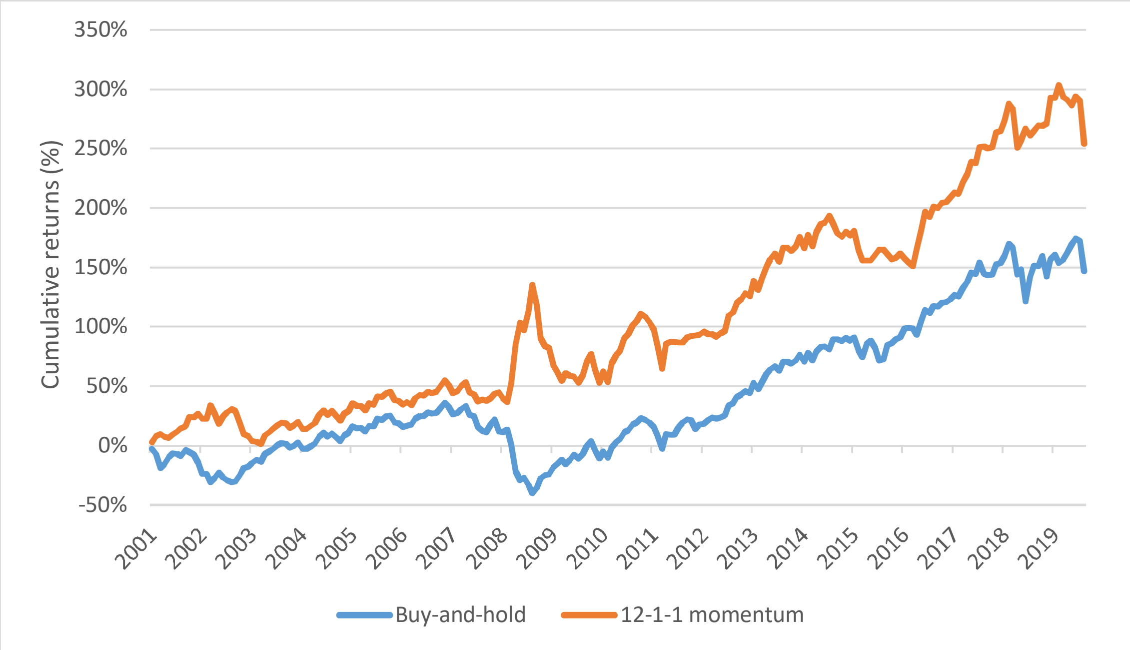

Figure 2. Cumulative excess returns of time-series momentum strategy.

Similarly to relative-strength strategies two subsamples are formed in order to further investigate the performance of the time-series momentum strategies during the financial crisis and post-crisis periods. The excess returns of both subsamples are adjusted with the FF3, FF5, and FF6 regression models. Table 12 presents the results of time-series strategies over the financial crisis period and the post-crisis period. Panel A in Table 12 presents the results from the post-crisis period of 1.3.2009-1.2.2020 whereas panel B presents the results from the financial crisis period of 1.10.2007-1.3.2009.

The results from the post-crisis period are consistent with the observations from figure 2 as each of the intercepts for all strategies are negative. However, all of the negative alphas are statistically not different from zero and thus no further implications can be made. Despite the steep upward slope shown in the cumulative excess returns in figure 2 during the time of the financial crisis, all of the risk-adjusted returns are negative except the positive but statistically insignificant alpha with the (1.1) strategy from the

FF6 model. Interestingly, both economically and statistically significant negative alphas can be observed from three strategies during the crisis period. From the FF5 model, the (7-1-1) and (9-9) strategies yield a negative abnormal return of -3.3% and -2.0% respectively and from the FF3 model, the (3-3) strategy has a negative abnormal return of -2.0%. The results indicate that these strategies are highly unprofitable during the crisis. Furthermore, the results from the crisis period together with a closer look at the cumulative excess returns imply that the good performance during the crisis period is only momentary.

Panel A: Post-crisis period				Panel B: Financial crisis period			
Strategy:	FF3	FF5	FF6	**Strategy:**	FF3	FF5	FF6
7-1-1				**7-1-1**			
Alpha	-0.002	-0.004	-0.004	Alpha	-0.023	**-0.033**	-0.028
	(0.488)	(0.249)	(0.185)		(0.067)	**(0.045)**	(0.155)
Rm - Rf	**0.228**	**0.285**	**0.388**	Rm - Rf	-0.314	**-0.603**	-0.572
	(0.011)	**(0.001)**	**(0.000)**		(0.107)	**(0.034)**	(0.056)
SMB	-0.057	-0.065	-0.020	SMB	0.838	0.973	0.912
	(0.691)	(0.651)	(0.869)		(0.133)	(0.091)	(0.134)
HML	0.110	-0.231	0.262	HML	**-0.620**	-0.532	-0.506
	(0.389)	(0.178)	(0.11)		**(0.02)**	(0.091)	(0.126)
RMW		0.102	0.197	RMW		0.105	-0.226
		(0.644)	(0.301)			(0.898)	(0.837)
CMA		**0.861**	**0.507**	CMA		-1.526	-1.327
		(0.002)	**(0.039)**			(0.127)	(0.231)
UMD			**0.460**	UMD			0.121
			(0.000)				(0.637)
R-square	0.067	0.139	0.375	R-square	0.536	0.648	0.656
12-1-1				**12-1-1**			
Alpha	-0.002	-0.003	-0.003	Alpha	-0.007	-0.008	-0.001
	(0.589)	(0.393)	(0.272)		(0.663)	(0.717)	(0.959)
Rm - Rf	**0.470**	**0.510**	**0.635**	Rm - Rf	**-0.803**	-0.748	-0.706
	(0.000)	**(0.000)**	**(0.000)**		**(0.005)**	(0.073)	(0.111)
SMB	0.048	0.006	0.060	SMB	-0.179	-0.076	-0.160
	(0.72)	(0.964)	(0.564)		(0.8)	(0.926)	(0.855)
HML	-0.208	**-0.491**	0.102	HML	-0.316	-0.330	-0.294
	(0.086)	**(0.003)**	(0.457)		(0.328)	(0.464)	(0.538)
RMW		-0.041	0.072	RMW		0.204	-0.248
		(0.845)	(0.651)			(0.869)	(0.882)
CMA		**0.686**	0.260	CMA		0.151	0.422
		(0.011)	(0.205)			(0.916)	(0.795)
UMD			**0.553**	UMD			0.165
			(0.000)				(0.672)
R-square	0.231	0.269	0.587	R-square	0.629	0.630	0.637
12-7-1				**12-7-1**			
Alpha	-0.003	-0.004	-0.004	Alpha	-0.002	-0.011	-0.003
	(0.24)	(0.175)	(0.162)		(0.92)	(0.696)	(0.938)
Rm - Rf	**0.554**	**0.574**	**0.625**	Rm - Rf	**-0.642**	-0.604	-0.555
	(0.000)	**(0.000)**	**(0.000)**		**(0.043)**	(0.203)	(0.273)
SMB	0.117	0.139	0.161	SMB	-0.487	-0.306	-0.405
	(0.349)	(0.286)	(0.199)		(0.565)	(0.753)	(0.697)
HML	-0.211	-0.284	-0.039	HML	-0.144	-0.016	0.027
	(0.06)	(0.067)	(0.812)		(0.704)	(0.976)	(0.962)
RMW		0.195	0.241	RMW		0.704	0.177
		(0.33)	(0.21)			(0.632)	(0.929)
CMA		0.152	-0.023	CMA		-0.443	-0.128
		(0.543)	(0.926)			(0.795)	(0.947)
UMD			**0.228**	UMD			0.192

			(0.001)				(0.677)
R-square	0.341	0.347	0.401	R-square	0.447	0.453	0.463
1-1				**1-1**			
Alpha	-0.001	-0.001	-0.001	Alpha	-0.014	-0.023	0.005
	(0.822)	(0.71)	(0.702)		(0.484)	(0.426)	(0.885)
Rm - Rf	-0.087	-0.078	-0.112	Rm - Rf	**-0.835**	-0.547	-0.375
	(0.318)	(0.379)	(0.211)		**(0.019)**	(0.27)	(0.43)
SMB	-0.052	0.048	0.033	SMB	0.447	0.605	0.260
	(0.712)	(0.74)	(0.816)		(0.629)	(0.557)	(0.792)
HML	0.213	0.306	0.144	HML	0.090	-0.093	0.057
	(0.091)	(0.077)	(0.449)		(0.828)	(0.868)	(0.915)
RMW		0.452	0.421	RMW		1.224	-0.619
		(0.044)	(0.058)			(0.434)	(0.743)
CMA		-0.202	-0.085	CMA		0.386	1.491
		(0.471)	(0.763)			(0.829)	(0.423)
UMD			-0.151	UMD			0.672
			(0.055)				(0.146)
R-square	0.028	0.061	0.088	R-square	0.393	0.445	0.555
3-3				**3-3**			
Alpha	0.000	0.000	0.000	Alpha	**-0.020**	-0.021	-0.020
	(0.94)	(0.962)	(0.971)		**(0.018)**	(0.056)	(0.145)
Rm - Rf	0.003	0.009	0.073	Rm - Rf	-0.247	**-0.437**	**-0.427**
	(0.972)	(0.908)	(0.316)		(0.052)	**(0.024)**	**(0.039)**
SMB	-0.126	-0.187	-0.159	SMB	**0.919**	**0.928**	**0.910**
	(0.295)	(0.139)	(0.176)		**(0.016)**	**(0.024)**	**(0.038)**
HML	0.117	0.123	**0.430**	HML	**-0.726**	**-0.786**	**-0.778**
	(0.278)	(0.411)	**(0.006)**		**(0.000)**	**(0.002)**	**(0.004)**
RMW		-0.121	-0.063	RMW		-0.331	-0.428
		(0.529)	(0.728)			(0.549)	(0.569)
CMA		0.040	-0.180	CMA		-0.611	-0.553
		(0.868)	(0.435)			(0.346)	(0.452)
UMD			**0.287**	UMD			0.035
			(0.000)				(0.838)
R-square	0.017	0.026	0.162	R-square	0.758	0.795	0.796
6-6				**6-6**			
Alpha	-0.001	-0.002	-0.002	Alpha	-0.001	-0.009	-0.004
	(0.567)	(0.415)	(0.321)		(0.882)	(0.073)	(0.461)
Rm - Rf	0.059	0.087	**0.170**	Rm - Rf	**0.148**	0.083	0.118
	(0.323)	(0.15)	**(0.001)**		**(0.05)**	(0.327)	(0.148)
SMB	**-0.226**	**-0.264**	**-0.228**	SMB	-0.027	0.069	0.000
	(0.021)	**(0.009)**	**(0.005)**		(0.894)	(0.695)	(0.998)
HML	0.002	-0.094	**0.299**	HML	-0.103	0.027	0.056
	(0.982)	(0.425)	**(0.005)**		(0.269)	(0.782)	(0.525)
RMW		0.003	0.079	RMW		0.508	0.141
		(0.983)	(0.519)			(0.076)	(0.652)
CMA		0.321	0.039	CMA		**-0.831**	-0.611
		(0.095)	(0.804)			**(0.019)**	(0.065)
UMD			**0.367**	UMD			0.134
			(0.000)				(0.085)
R-square	0.042	0.079	0.418	R-square	0.295	0.601	0.708
9-9				**9-9**			
Alpha	-0.003	-0.003	-0.003	Alpha	-0.010	**-0.020**	-0.014
	(0.212)	(0.191)	(0.137)		(0.08)	**(0.016)**	(0.121)
Rm - Rf	**0.136**	**0.152**	**0.227**	Rm - Rf	-0.018	-0.032	0.006
	(0.036)	**(0.022)**	**(0.000)**		(0.84)	(0.789)	(0.96)
SMB	-0.165	**-0.225**	**-0.192**	SMB	0.133	0.264	0.188
	(0.116)	**(0.039)**	**(0.041)**		(0.605)	(0.311)	(0.463)
HML	-0.175	-0.245	0.113	HML	**-0.522**	**-0.459**	**-0.425**
	(0.063)	(0.058)	(0.363)		**(0.000)**	**(0.006)**	**(0.01)**
RMW		-0.131	-0.063	RMW		0.637	0.230
		(0.428)	(0.662)			(0.119)	(0.636)
CMA		0.234	-0.023	CMA		-0.658	-0.414
		(0.262)	(0.903)			(0.16)	(0.387)
UMD			**0.333**	UMD			0.149
			(0.000)				(0.204)
R-square	0.060	0.082	0.318	R-square	0.660	0.750	0.789
12-12				**12-12**			
Alpha	-0.003	-0.003	-0.003	Alpha	-0.004	-0.007	-0.003

	(0.196)	(0.163)	(0.156)		(0.394)	(0.338)	(0.77)
Rm - Rf	0.093	0.109	**0.139**	Rm - Rf	0.106	0.037	0.065
	(0.107)	(0.064)	**(0.018)**		(0.201)	(0.762)	(0.61)
SMB	-0.162	**-0.210**	**-0.197**	SMB	0.242	0.298	0.243
	(0.084)	**(0.029)**	**(0.037)**		(0.308)	(0.261)	(0.372)
HML	-0.097	-0.206	-0.061	HML	**-0.476**	**-0.469**	**-0.445**
	(0.245)	(0.071)	(0.624)		**(0.000)**	**(0.006)**	**(0.01)**
RMW		-0.150	-0.122	RMW		0.030	-0.268
		(0.308)	(0.397)			(0.939)	(0.601)
CMA		0.320	0.215	CMA		-0.349	-0.171
		(0.085)	(0.244)			(0.446)	(0.73)
UMD			**0.136**	UMD			0.108
			(0.009)				(0.368)
R-square	0.041	0.075	0.125	R-square	0.635	0.666	0.693

Table 12. Subsample results of time-series strategies.
The table reports the subsample results of time-series momentum from the FF3, FF5, and FF6 model regression for the financial crisis period of 1.10.2007-1.3.2009 and post-crisis period of 1.3.2009-1.2.2020. Panel A presents the results from the post-crisis period and panel B from the financial crisis period. The p-values of the respective coefficients are reported in parentheses and the significance levels at 5% are bolded.

The results from the FF3, FF5, and FF6 regression models clearly show that the null hypothesis holds and cannot be rejected for the time-series smart beta ETF momentum strategies. The (12-1-1) strategy is able to yield a positive abnormal monthly return of 0.618% at the 5% significance level from the FF3 model regression. However, the abnormal return of the (12-1-1) strategy is insignificant and not different from zero from the FF5 and FF6 model regressions. Moreover, the success of the (12-1-1) strategy is driven by the high performance accrued during the financial crisis period of 2007-2009. However, the abnormal returns during the financial crisis subsample period are insignificant and negative and during the post-crisis period, the momentum strategy is outperformed by a simple buy-and-hold strategy.

For the other strategies, the observed alphas are all insignificant from the three regressions applied in this thesis. Thus, the results prove that investors are not able to achieve positive abnormal returns by implementing time-series momentum strategies in smart beta ETFs over the sample period. The results remain the same for the subsamples of the financial crisis and post-crisis periods. Furthermore, statistically significant alphas can be observed from the long-only (7-1-1), (9-9), and (12-12) strategies when considering the long-only and short-only portfolios individually. However, the abnormal returns of these long portfolios are all negative and less than -

0.2%. Thus, the time-series momentum remains unprofitable even if the momentum strategy takes only long or short positions in smart beta ETFs.

In terms of raw returns, the performances of the smart beta ETF time-series momentum strategies reported in this thesis are consistent with previous results of time-series momentum in sector ETFs reported by Tse (2015). Similarly to Tse (2015), the results discussed in this chapter show that the time-series momentum profits are mainly achieved during the financial crisis period and that the profits vanish soon after the crisis. In addition, the abnormal returns during the post-crisis period are all statistically insignificant. Thus, the results presented in this thesis extends the findings of Tse (2015) to smart beta ETFs and confirms that the results remain the same with a longer post-crisis sample period. Furthermore, the time-series momentum returns are statistically insignificant when adjusted with the FF3 model similarly to Tse (2015). The results presented in this chapter are also in sharp contrast with the significant results of time-series factor momentum documented by Ehsani & Linnainmaa (2019). For instance, Ehsani & Linnainmaa (2019) report significant alphas of 1.39% (t-value = 4.94) and 0.29% (t-value = 2.53) from the FF5 and FF6 models respectively for time-series momentum strategy that is long on factors that have positive returns over the past year and short on factors that have negative returns over the past year.

The reasons behind the failure of ETF momentum strategies reported in the thesis over the stock and factor momentums might be similar as discussed in Tse (2015). Firstly, the failure of factor momentum strategies in ETFs might be due to the simplistic factor approach of the smart beta ETFs. Smart beta ETFs failure to capture the intended factors could explain the differing results with the factor momentum strategies in individual stocks. Secondly, in recent decades the stock markets might have been more efficient than before or the ETF markets are more efficient in general than the stock markets. For instance, Arnott et al. (2019) use a factor sample period that covers the years of 1963-2016, and Ehsani & Linnainmaa (2019) use a sample of 1963-2015 when this thesis only concentrates on the two most recent decades. Thirdly, the small difference between the winner ETFs and loser ETFs due to the high correlation across the ETFs might be the reason for the failure as momentum is based on the spreads between the winners and losers (Ehsani & Linnainmaa 2019).

7 Conclusions

The purpose of this thesis is to examine the profitability of momentum strategies in smart beta exchange-traded funds. Moskowitz & Grinblatt (1999) show that industry momentum provides significantly higher profits than individual stock momentum initially documented by Jegadeesh & Titman (1993). Tse (2015) extends industry momentum into the field of exchange-traded funds by implementing momentum strategies in sector ETFs and finds no significant momentum profits over the period of 1999-2014. However, more recent studies conducted by Arnott et al. (2019) and Ehsani & Linnainmaa (2019) suggest that industry and stock momentums are actually by-products of factor momentum. Implementation of momentum strategies generates substantially large transaction costs due to the high trading volume required by these strategies. Exchange-traded funds could offer investors an opportunity to implement momentum strategies with lower trading volume and transaction costs. Thus, the aim of this thesis is to examine whether momentum strategies can be exploited profitably in smart beta exchange-traded funds.

Inspired by Tse (2015), Arnott et al. (2019), and Ehsani & Linnainmaa (2019) the profitability of smart beta ETF momentum is examined through both relative-strength and time-series momentum strategies. The data sample comprises 24 smart beta ETFs traded on U.S markets that invest in six different factors over the sample period of August 2000 – February 2020. The alphas of the smart beta ETF momentum strategies are computed from three regressions of the Fama-French 3, 5, and 6-factor models in order to test the null hypothesis: smart beta ETF momentum strategies are not able to provide statistically significant and positive abnormal returns.

The results of relative-strength momentum strategies clearly show that the null hypothesis holds and cannot be rejected. The alphas of the momentum strategies are all negative and statistically insignificant at the 5% significance level. The only statistically significant alpha can be observed from the strategy with one-month ranking and holding periods but the abnormal monthly return is negative -0.6%. The insignificant results are consistent with the results reported from previous studies of sector ETF momentum (Du et al. 2014; Tse 2015). Moreover, the results are in sharp contrast with the significant results of relative-strength factor momentum documented by Arnott et al. (2019).

The null hypothesis holds also for the time-series momentum strategies as all of the positive abnormal returns are statistically not different from zero. The strategy with the ranking period of one year skipping the most recent month and the holding period of one month is able to yield a significant abnormal return from the Fama-French 3-factor model regression. However, the abnormal returns are statistically insignificant after adjusting with the Fama-French 5 and 6-factor models. Moreover and similarly to Tse (2015) the results imply that ETF momentum profits are mainly driven by the higher performance accrued during the financial crisis period and thereafter momentum strategies are outperformed by a simple buy-and-hold strategy. The results extend the findings of Tse (2015) to smart beta ETFs and confirm that the momentum strategies remain unprofitable with a longer post-crisis sample period. The results of time-series momentum are also in sharp contrast with significant results of time-series factor momentum reported by Ehsani & Linnainmaa (2019).

Under the presented results and evidence, this thesis concludes that smart beta ETF momentum strategies are unprofitable and investors are not able to achieve abnormal returns by exploiting these strategies. The reasons behind the failure of ETF momentum strategies reported in the thesis over the stock and factor momentums might be similar as discussed in Tse (2015). First, the possible failure of smart beta ETFs to capture the intended factors could explain the differing results with the factor momentum in individual stocks. Second, ETF markets might be more efficient in general than the stock markets. Third, the small spreads between the winners and losers due to the high correlation across the ETFs might be a reason for the failure. Future research could try to explain more comprehensively the reasons behind the momentum effect discrepancies between ETFs and individual stocks.

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