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# Time-Series and Cross-Sectional Price Momentum

*An Empirical Study at the Oslo Stock Exchange*

**By Vidar Kogstad Nygaard**

**Supervisor: Petter Bjerksund**

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# Abstract

This thesis investigates the effects of a simple time-series momentum overlay either as a stand-alone approach or in combination with cross-sectional price momentum strategies from the period 1985 to 2015 at the Oslo Stock Exchange. I first construct and evaluate a set of sector, market indices and long-only cross-sectional stock/sector momentum portfolios. I find robust and persistent cross-sectional momentum effect both in individual stocks and sectors at the Oslo Stock Exchange. Then I explore the effects of time-series momentum applied to each constructed portfolio. I document that the application of time-series momentum to an existing sector or market portfolio can deliver a substantial improvement in profitability with a significant decrease in volatility and drawdowns. The combination of cross-sectional and time-series momentum is shown to improve results relative to either strategy alone. Together the findings suggest practically feasible trading strategies with significant potential for abnormal returns.

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# 1. Introduction

Can we systematically outperform the market? Very few investors do and research repeatedly show that replicating the market index, e.g., buy and hold of a passively managed low cost fund or Exchange Traded Fund for the majority of investors is the most rational way to earn maximum risk-adjusted equity returns (Ang, Goetzmann & Schaefer (2016)). Presumably, this passive buy and hold strategy also have the potential to mitigate investor biases while at the same time also deliver the greatest diversification benefits. Studies looking at mutual fund performance maintains this view by declaring a consistent underperformance compared to the benchmark or "market" portfolio. Over 80 percent of all domestic US equity funds have over the past three years failed to beat the benchmark[1], the S&P 500 index. While this figure can seem like an outlier, it represents a typical pattern since the first mutual funds entered the scene. Findings from the Norwegian mutual fund industry is no less sobering. Qvigstad (2009) documents that mutual fund managers at the Oslo Stock Exchange have been unable to deliver any statistical evidence for systematic alpha and, quite to the contrary often underperforms compared to the benchmark. Even if the fund have succeeded, the fees charged can not justify the gains, making it inferior to a passive benchmark investment on a net basis. Yet, as the objective of a mutual fund manager is to outperform the benchmark, there is actually only a very slight leeway to deviate much from the index, i.e., only a small tracking error is allowed (Clenow (2014)). Thus, the actively managed part of a mutual fund is in practice highly limited (see e.g., Ibbotson & Kaplan (2000) and Brinson, Singer & Beedower (1991))

In the topical debate between active and passively managed equity (fund) management, one of the most influential ideas framing the discussion have been the Efficient Market Hypothesis (EMH). In its strongest form, the EMH conveys that observed stock prices are a full reflection of all relevant publicly available information. Even in its weakest form, the basic implication of EMH is that any attempt to consistently outperform the market is a futile endeavor at best. Certainly not without merit, EMH presently is thought and has been a standard curriculum in most business schools across the globe not long after the publication of its first formal arguments; initially by Samuelson (1965), then given structure and

[1] Refer to : https://us.spindices.com/resource-center/thought-leadership/research/

operationalized by Roberts (1967) and famously Fama (1970). In the 1970s and 1980s the static market view declared by the EMH had an almost dogmatic grip but have in recent decades increasingly been scrutinized for its potential limitations (Antonacci 2014). The emergence of behavioral finance have empirically shed light on the many ways in which investors have a tendency to depart from rational behavior, i.e., maximizing their own best self-interest, while simultaneously making emotional or irrational choices on a systematic and sometimes predictable scale. A growing body of research argues that the assumption of utility optimization in many cases can be replaced by simple heuristics adapted by investors through time and experience. (Greyserman & Kaminski, 2014). Implications of these emerging theories and empirical findings are that prices systematically can and do depart from their fundamental values, thus leaving the existence of persisting market anomalies a potential reality. One such anomaly, known in academic circles as cross-sectional momentum, or what practitioners have called "relative price momentum" since it was coined by Levy (1967), became a heavily researched phenomena in the early 1990s. Cross-sectional momentum, i.e., comparing the performance of an asset relative to its peers, arguably became highly popularized by the paper "Returns to buying winners and selling losers: Implications or Stock Market Efficiency" published by Jagadeesh and Titman (1993). In more recent studies, cross-sectional momentum have persistently continued to display a robust performance, not attributable to the known risk factors (Fama, 2004). A number of empirical studies have investigated cross-sectional momentum in the Norwegian stock market using the same or a similar approach as Jagadeesh & Titman (1993), i.e., a simultaneous long (buy) and short (sell) position with intermediate term portfolio rebalancing (3-12 months). In aggregate, these empirical investigations find statistical evidence for the profitability of cross-sectional momentum and often attribute this finding to the short-side of the trade. However, the evidence for abnormal returns for only trading the long-side in the cross-section are limited. For most investors, initiating short positions are subject to either operational and/or institutional limitations. In addition, recent momentum strategies often use monthly rebalancing (Antonacci 2014). Accordingly I present the following research question:

*Research question 1: Is a cross-sectional price momentum strategy based on initiating a long position in the past winning stocks over the intermediate term able to deliver significant abnormal returns ?*

Moskowitz & Grinblat (1999) documents a strong cross-sectional momentum effect by initiating a long position in the prior winning industries and a short position in the prior losing industries. To this date, I can not find published research or otherwise empirical evidence for cross-sectional sector/industry momentum effect at the Oslo stock exchange. As cross-sectional momentum strategies are prone to significant transaction costs and a more a labor-intensive endeavor than trading single ETFs, momentum based on industries/sectors would more easily be implemented and with considerably lower transaction costs (at least with the availability of representative securities). Thus,

> *Research question 2: is a cross-sectional price momentum strategy based on initiating a long position in the past winning sector(s) over the intermediate term able to deliver significant abnormal returns?*

Given the prevailing status of the EMH in the history of finance and modern portfolio theory, strategies that are governed by historical price movements and thus bluntly contradicting the EMH, have traditionally fallen under the label of "Voodoo Finance" (Greyserman & Kaminski 2014). Although cross-sectional momentum now have been accepted by most scholars, this tendency could explain why time-series momentum, or what some practitioners call "absolute momentum", that is comparing the trend of an assets own past performance with its present performance, not until recently have received much attention by academics. Few to none relevant studies have been published on the application of absolute, time-series momentum on stocks/sectors/indices the at the Oslo Stock Exchange (OSE). Even in the international literature (mostly in the US), most studies conducted thus far have focused on absolute, time-series momentum across different sets of asset classes. The abnormal returns generated by relative, cross-sectional momentum does little to mitigate risk or downside exposure. In addition, as this strategy deals with individual stocks, the number of transactions and the related costs can be substantial. In the paper "Absolute Momentum: A Simple Rule-Based Strategy and Universal Trend-Following Overlay" by Antonacci (2013), it is documented that a simple strategy based on absolute momentum, unlike cross-sectional momentum, significantly mitigates the downside volatility related to long-only investing. Absolute momentum does this by protecting from downturn markets. As the implementation of this rules-based strategy is simple and associated with low transaction costs, it could potentially be a promising addition to institutions and retail investors alike. Thus, the main research question is the following:

*Research question 3: To what extent can a simple rule-based time-series overlay applied to stocks at the Oslo Stock exchange deliver significant abnormal returns ?*

Antonacci (2014) argues that cross-sectional and time-series momentum both have distinct advantages and that they for the most part are uncorrelated, hence we can combine cross-sectional and time-series momentum in order to gain the advantages of both. Thus, related to the main research question, I formulate the following:

*Research question 4: What are the effects combining a simple rule-based time-series overlay to a cross-sectional individual stock momentum strategy ? What are the effects combining a simple rule-based time-series overlay to a cross-sectional sector momentum strategy ?*

This thesis investigates different cross-sectional, absolute momentum and combinations of thereof, called dual momentum, using stocks listed at the Oslo Stock Exchange. The cross-sectional momentum strategies constructed contrasts most prior studies conducted on the OSE that mostly are based on the methodologies accounted for in Jagadeesh & Titman (1993). I document robust long-only cross-sectional momentum alpha for individual stocks and sectors at the OSE. The time-series momentum strategies are also shown to deliver persistent abnormal returns relative to the market portfolio with the benefit of dramatically reduced volatility and much more feasible practical implementation for the average investor.

Following this introduction, chapter 2 will present some of the theoretical underpinnings behind market mechanics, distinctions of the momentum strategies, a review of relevant prior research and related financial theory. Chapter 3, will explain the data collection and handling process, steps to mitigate behavioral biases, the portfolio construction methodologies and performance evaluation. Chapter 4 presents the backtests and robustness checks for all of the constructed portfolios. Chapter 5 close with a discussion of the findings, implications, weaknesses and suggested directions for future studies.

# 2. Literature Review

The statistical performance of cross-sectional and time-series momentum, represents an alternative to the passively managed buy and hold paradigm. This also facilitates the need to advance upon the static EMH framework with a more dynamic understanding of how markets evolve and adapt. Section 2.1 and 2.2 in this chapter begins with a discussion of the Efficient market hypothesis and the adaptive market hypothesis.. Section 2.3 presents momentum definitions, theory and empirical background. Section 2.4 Gives an overview of some related theories in financial economics.

## 2.1 Efficient Markets

Paul Samuelson´s (1965) publication "Proof that properly anticipated prices fluctuate randomly", describes that the percentage moves of stock prices follow a geometric Brownian motion, I.e., a random walk behavior. Building on the mathematical notion he states that price changes must be impossible to forecast given that the market in which they originate are informationally efficient. Samuelson explicitly states in his paper that the established theorem in itself not was a proof that competitive markets work well. Additionally he did not have any interest in investigating if in fact the markets did work well (Fox, 2009). Samuelson (1965) have frequently been cited as the origin of the EMH. A supreme Interest in synthesizing and proving such a claim however was very real at the Chicago business school at that time. The Chicagoans had grown an almost uniform conviction that the development of stock prices approached a random predictable perfection (Fox, 2009). Through what eventually mounted to thousands of event studies, examining the efficiency of which the market was able to incorporate information through its prices, the conviction grew to a dogmatic view of market dynamics where no doubt could be casted on the "fact" that the prices in fact were a highly reliable reflection of old, new and often well-hidden information. Eugene Fama studied the works of Harry Markowitz, Bill Sharpe and John Lintner and it quickly became apparent to him that the apparently disparate versions of CAPM, really meant the same thing. Fama realized that his theory of efficient markets had to be integrated with the CAPM for it to have any substantial meaning. (Fox, 2009). This joint relationship was published by Fama (1970) "Efficient capital markets: A review of theory and empirical work", where he cited the mounting studies undergone in the previous decade pointing to the notion that markets hardly could be predicted and halted with the statement that evidence contradicting the efficient market hypothesis was slim. Going back in time, Harry Roberts (1967) was the person that initiated his peers at Chicago define the exact meaning behind the efficient market term which was at a later time redefined by Eugene Fama:

I. Weak market efficiency: This was in essence the random walk hypothesis, I.e., one can not expect to beat the market by using its past prices

II. Semi-strong market efficiency: one can not outperform the market by using any information available to the public

III. Strong market efficiency: one can not outperform the market even by using "private information"., I.e., relevant information that is not accessible to other investors.

Although nuanced, these three classical types of EMH in general follow the same course: In an active and publicly traded marketplace, all available information are at all times reflected in the prices. The informational efficiency implies that the higher the competition for profit the more efficiently information is incorporated and consequently the more random future price changes will become as it can not be on the basis of already priced historical information. This is a result of extensive competition among armies of investors seeking profitable opportunities, driving arbitrage profits to zero (Ang et al, 2009). Thus, no mispriced assets exists as the forces of supply and demand are thought to be so prevalent that they move faster than any single agent themselves can expect. To reiterate, the general implication of the EMH is the vain pursuit of attempting to profit from historical data.

In the earlier refinements of the EMH the neo-classical assumptions entered the framework where now prices changes weighted for their appropriate utility functions., e.g., constant relative risk aversion, must be impossible to forecast (Lo, 2004). Under this framework prices are efficient when all investors have "rational expectations". More recent extensions have added realism through e.g., transaction, information and agency costs state dependent preferences, information asymmetry (Ang et al, 2009). Lo (2004) argues that the current theoretical intuition behind the EMH framework can be summarized through the "three Ps" inherent in the principle of supply and demand: prices, probabilities and preferences: The aggregate demand curve is a product of the optimized preferences of individuals based on prices (amongst other demand factors), while the aggregate supply curve is a product of the optimization of the producers preferences constrained by prices (amongst other supply factors). Simultaneously, consumption and production planning depends on assigning implicit or explicit probabilities to uncertain future outcomes. In addition to being fundamental to economic decisions under uncertainty , modern asset pricing models rely on the three Ps in arriving at "equilibrium" (Lo 2004). The simultaneous interplay between prices, preferences and probabilities give the analysis of financial economics problems a rich depth while also yielding a set of theoretical and empirical implications. We can understand and test the underlying assumptions of the EMH through different empirical tests on the three Ps (Loo 2004).

Ang et al (2009) conducted a review of the prevailing evidence for efficient markets was undertaken as a scientific justification for or against active fund management. In this report EMH tests are divided into price tests and tests on investment managers and institutions. The former usually constructed as back-tests on historical price samples while the latter in a real institutional investment or trading environment. Other tests on the validity of the EMH have been conducted on behalf of the implicit probability assumptions implicated in asset pricing (see Lo 2004). However the most pervasive rebuttal is perhaps found in the empirical research conducted by psychologists surrounding the formation of preferences. This ongoing research contradicts the validity of the classical economic assumption of rational and utility maximizing market agents.

### 2.1.1 Tests on efficient markets: Prices and Institutions

Based on a large body of research on the degree to which the market was able to incorporate information through its prices, the Chicagoans around the 1970s landed on a satisfying consensus surrounding the existence of weak form efficiency. The deceptively intuitive and simple notion behind the EMH paradigm increasingly became challenged as it gradually faced skepticism (see e.g., Fox(2009), Antonacci (2014), Ang et al (2009)). This led to scores of studies in search for evidence contradicting the hypothesis. The initial tests on serial-correlation in returns frequently exhibited some evidence of future predictability in historical returns. These studies in the latter part of the last century generally was ignored in favor of the compelling conviction of efficient markets. findings in opposition to the stocks CAPM "beta" (and hence efficiency), was called an "anomaly". Later anomalies was labeled relative to multi-factor models such as the Fama-French Three factors: Market, Size and Value and later momentum. Gradually a series of different anomalies started to poke holes in assumptions of random walk and informational efficiency: from the small firm effect, the

January effect, earnings ratio effect, short and long term mean reversion, earnings announcements and as will be discussed in greater detail in section 2.3, momentum. More recent documented anomalies is stocks with high idiosyncratic volatility and low returns, investor sentiment pricing, low returns in high distress stocks and recent examples of anomalies caused by information flow lags, clearly contradictory to the EMH. The caveat with most of these anomalies and their implications to the EMH is that they are based on back-testing and not actual real life returns (Ang et al, 2009). Looking at real life ”tests”, for mutual funds no statistical evidence for systematic positive alpha generated by the mutual fund manager is identified (see Fama French (2008), Wermer (2000)). Sparse evidence also exists for the institutional and sovereign wealth funds, however, some evidence for positive alpha exists for different endowment funds and Hedge funds, albeit the latter with less reliability data quality (Ang et al, 2009).

## 2.2 Adaptive Markets

New discoveries contradicting rationality assumptions, dozens of new market "anomalies" uncovered, financial crisis, exogenous interventions, record high volatilities and erratic asset behavior. These and more are all a part of the present economic environment. The framework in which most financial professionals and investors are trained now seems incomplete and inadequate as a narrative explanation or as a reference for future guidance (Lo 2012). Globalization, population growth, GDP growth, informational flow, technological innovations and more, have in the recent decades fundamentally altered the complexity of the economic and financial landscape. Because of this, we now observe significant error approximations in our traditional investment assumptions, e.g., linearity in the risk - return space, stationarity etc.

> *"Contrary to current popular sentiment, the EMH is not wrong: it is merely incomplete." (Lo 2012, 1)*

The adaptive market hypothesis (AMH), although still in its infancy, is a new perspective consistent with EMH as well as theories from behavioral finance. Early evidence indicate that AMH can explain both the inherent behavioral implications when markets depart from EMH as well as the shift back to "efficiency" (Lo 2012).

In the context of this thesis, AMH serves both as a useful reference to comprehend prior departures from efficiency in general, but also perhaps most importantly, to give a more intuitive understanding of dynamic trading strategies such as cross-sectional and time-series momentum.

### 2.2.1 Economic environments - From Physics to Evolutionary Biology.

Around the mid 1950s, the contemporary pioneers was in search of central theoretical features and first principles, much like in physics, that could be established "truths" in finance and economics. The hyper rational traditional investment paradigm is a result of the assumptions and propositions put forth from this era.

Today, scientific evidence from disciplines such as psychology and neuroscience clearly indicates that a limited number of heuristic principles, as opposed to rational utility maximization, often is a dominant assessment and prediction tool for decision making (Rational). These heuristics are a natural consequence of adaption through the need for survival. Although highly useful in the context in which they originated, simple heuristics can often lead maladaptive behavior or "biases", e.g., fear, greed and overconfidence (traits that all have increased survival) in the context of financial markets. Thus, humans, generally intelligent, competitive and forward looking species, have a highly complex decision-making apparatus, both capable of "neocortical" (and in the same sense neo-classical) long term rational decision making but also often are prone to instinctive behaviors originating from the primal physiological structures such as the brain stem, limbic system and cerebral cortex (Kahneman, 2012). For example, one can easily see how the fight and flight response can lead to financial disaster in the context of financial decision making. In light of this realization .efficient and irrational markets both reside on the extreme ends on a continuum, neither in tune with the actual state of the market. The AMH focuses on the *collective behavioral response* under different market conditions (Lo 2012) and as a consequence approach the evolution of markets in the context of the principles of evolutionary biology and natural selection. Lo (2004, p18) writes: "*Prices reflect as much information as dictated by the combination of environmental and the number and nature of "species" in the economy….or ecology.*" Under this view, "species" are the different economic agents interacting in the market, e.g., retail and institutional funds, market-makers. We can describe the business cycle under the AMH framework as an environment where initially a small amount of species competing for an abundant resource is an environment characterized by certain profit opportunities (a positive alpha), low expected efficiency and less fierce competition. As the these resources become increasingly scarce, competition increases.

When multiple species in a certain market is in competition for quite scarce resources, we would expect that market to be highly efficient (a zero alpha). In this environment, the most adaptive species will survive many will be extinct, thus decreasing the level of competition and starting the cycle yet again (Kaminsky and Greyserman, 2014)

Going back to the perspective of aggregate behavior, the heuristics can be learned and highly subjective. However, they are often they universal in the sense of their general direction and practical realization. For example in a collective fight or flight situation such as during the financial crisis, 2007-08, e.g., "panic sales". Thus, Lo (2004) argues that it is precisely the size of the population making biased decisions, i.e., using counter-intuitive heuristics in a inappropriate environment that determines their impact. Our heuristics might be sufficient in one environment while highly counter-productive in another. We can see that under a dynamic framework such as the AMH, arbitrage profits in certain markets can exist or arise relative to the location on the continuum between efficiency and irrationality. Also related to this is the time-varying nature of the relationship between of volatility, the risk premium and hence the risk-reward relationship.

### 2.2.2 Dynamic trading strategies and adaptation

Strategies that are able to adapt to changing environments will survive and thus reap the potential (and fleeting) alpha benefits inherent in less efficient market conditions. Kaminsky & Greyserman (2014) divide such factors affecting economic agents' ability to adapt into three major categories. I) Institutional factors: varying with the degree to which the agent is affected by political and institutional frictions and regulations, e.g., short sales restrictions, as is case for both Norwegian and most international mutual funds, Allocation and collateral constraints, Risk limits etc. II) Market functionality: different markets have different characteristics from contract standardization, the number and diversity of participants, counter-party risk. Thus market participants will face varying liquidity, asymmetries and counter-party risks in different markets. III) Behavioral biases: Trusted Heuristics developed through time can lead to inflexible behavior and thus be a crucial hindrance in adapting to changing market environments. Of the behavioral biases, Kaminsky and Greyserman (2014) lists four that are crucial to adaptation under crisis; Long equity bias, loss aversion, anchoring and herding.

## 2.3 Momentum: Context and empirical background

This section begins with defining the different types of momentum and its distinctions. Next follows a review of the empirical evidence on cross-sectional and time-series momentum. The chapter ends with a discussion of possible rationale behind the momentum effect.

### 2.3.1 Distinctions

In general, the momentum effect is the tendency for investments that has performed well(poor) for a certain period to have a greater likelihood of continuing to perform well(poor) than to turn around in the subsequent period. In addition, an investment which speed of over(under) performance have been greater relative to other investments, are expected to move up(down) relatively faster (see e.g., Antonacci 2014, Clenow (2014), Chincarini & Kim (2006), Berger. Israel & Moskowitz (2009)). Momentum refers to positive auto-correlation and we expect the winners(losers) to persist being winners (losers), thus we buy (sell) higher highs(lows). In addition to this general characterization, a few additional distinctions is due: momentum does have a number of different meanings both between practitioners and academics but also as a general term that sometimes loosely are referred to as any kind of high performing securities. Practitioners have traditionally used the term "Relative-Strength", meaning the same as what academics now call "cross-sectional momentum" or just "momentum" (although that term traditionally have meant something different to practitioners). Another form of momentum, often in practice called "trend following" or "absolute momentum", is what academics now label "time-series momentum". Bearing in mind these differences and the notion that all types of momentum in practice are based on time-series, I will in the subsequent chapters use the academic terms. Cross-sectional momentum refers to slicing a certain market of traded securities into segments and comparing the relative performing strength between them, strongest to the weakest. On the other hand, instead of comparing one asset to another, Time-series Momentum are comparing the performance of an asset to itself.

### 2.3.2 Academic papers

The momentum effect can be said to be one of the most pervasive and indisputable financial phenomena of our time. Price momentum has been documented in both in stocks but also for most liquid asset classes in different markets and countries (Aasnes, Moskowitz & Pedersen, 2013). Kaminski and Greyserman (2014) documents time-series momentum going back 800 years. Looking at cross-sectional momentum research, the study by Levy (1967) and others were criticized for not accounting for transaction costs and other implementation issues. However Akemann and keller (1977) demonstrated superior "relative strength" results after transaction costs for S&P 500 industry groups from 1967 - 1975. Next, Bohan (1981) found a strong "relative strength" momentum effect on the industry level In US stocks. Later Brush and boles (1983) looked at the past 18 years on the S&P 500 and found significantly t-statistics with returns of 15.2% compared to 5.9 %, using relative strength momentum. However it was not until the seminal paper by Jagadeesh & Titman (1993) was published, that research into the momentum effect really had sparked an interest in scholars[2]. The strategies in this paper implicitly set the stage to tackle many investor behavioral biases by using a set of mechanical, i.e., non-discretionary trading rules . Looking at daily stock returns on the NYSE and AMEX going back from 1965 to 1989, they constructed a set of 16 portfolio strategies based on the returns during the past j = 3, 6, 9 or 12 months , "look back" period while holding these portfolios for either k = 3. 6, 9, 12 months. Based on the returns during the j-months, a set of ten decile portfolios was constructed, I.e., the 10 % worst performing in the top decile and the 10% decile in the bottom decile. Using monthly rebalancing they initiated a long position in the bottom decile and a simultaneous short position in top decile. Positions are closed out at month t-k. Jagadeesh & Titman (1993) clearly demonstrated statistical evidence for trading stocks with a 3 to 12 month look-back period also performed relatively

better than their peers in comparative future periods. In closing, the authors attributed the excess returns to an investor under-reaction to firm-specific information/news. The findings in Jagadeesh and Titman (1993) was later verified out of sample by Jagadeesh & Titman (2001). The authors at this stage found the magnitude and continuation of statistical excess-returns noteworthy as other well-known anomalies such as the size effect not have been able to demonstrate such persistence. This persistence have continued up until this day with an apparently almost universal applicability (Antonacci 2014).

Most prior research on momentum have traditionally used a long position in the e.g., top 10-30% performers and a short position in the bottom 10-30%, forming a market neutral or

[2] over 300 papers on momentum have been published since this ground-breaking paper was released. Momentum is today one of the most heavily research finance topics (Antonacci 2014)

"zero cost portfolio". This way the short positions hedge the long positions and thus making either down or up markets viable. Related to this since cross-sectional momentum is based on the relative returns between assets and the fact that for example stocks tend to be highly correlated in bear markets, Antonacci (2012) points out that using a long-only cross-sectional momentum strategy likely will lead to losses in concert with the general downtrending market. Thus, especially for long-only strategies, we would like to be long only when both time-series and cross-sectional is positive[3]. One way to operationalize this is through the addition of a time-series (same an absolute or trend-following) overlay. For this, Antonacci (2012) determines to stay in the selected asset (T-bills) if the asset have out(under)performed treasury bills over the past year. This way T-bills act as a "safe harbor" until we have positive momentum again in both cross-sectional and time-series momentum. Antonacci (2012) uses both cross-sectional and time-series momentum applied to foreign/US Equities, high yield/credit bonds, equity/mortgage REITS, and gold/treasury bonds, demonstrating significant excess returns. However, in a more recent work, Antonacci (2014) applies the combination of cross-sectional and time-series momentum using stocks only. Here, staying invested in cross-sectional stock momentum (T-bills) if the prior 12 month returns of the S&P500 less the T-bill rate is positive (negative). This strategy of combining both cross-sectional and time-series momentum is called "dual - momentum", is shown to substantially outperform both time-series or cross-sectional stock momentum used alone. The dual momentum strategy exhibit significant alpha (t-statistic 2.67) regressed against a five-factor model Carhart - four factor and an bond index factor). A paper by Faber (2010) also constructed both a cross-sectional stock momentum strategy and a combination of such with and without a time-series overlay using US equities from 1928 to 2009. The rationale behind the time-series overlay is also here to avoid the great drawback of a cross-sectional momentum long only strategy, exposure to the beta risk of that particular asset class at all times. The long only cross-sectional momentum strategy showed robust return performance with similar volatility as the benchmark, while the same strategy with the added time-series overlay has kept the upside associated with a long only strategy with much less drawdowns and volatility [4]

[3] Antonacci actually uses the term "absolute momentum" which especially in this context makes more intuitive sense.

[4] Also see "A quantitative approach to tactical asset allocation" Faber (2013) for additional asset class implementation.

In addition to the traditional equity based cross-sectional strategies in the literature, time-series momentum (applied in some of the studies in the discussion above), have more recently proven to be equally as pervasive, even going back centuries (see e.g., Aasnes et al (2013), Kaminsky & Greyserman (2014)). Up until now the conducted research on time-series momentum have looked at broad asset classes or as a dynamic filter mechanism ( Antonacci (2012), Antonacci (2013), Antonacci (2014)). However, a recent paper (DSouza, I., Srichanachaichok, V., Wang, G. J., & Yao, C. Y. (2016)) documents evidence for a solid presence of time-series momentum by using a rudimentary time-series momentum strategy on individual stocks. In addition to finding significant and robust profits in the U.S, they also documented strong evidence for significant abnormal returns in the Norwegian as well as 10 of the 14 major international stock markets studied. Cross-sectional momentum strategies need a minimum of two assets and depend on a continual elimination and replacements of assets in the portfolio. Time-series momentum on the other hand, can be applied to even just one asset and as long as the trend remains positive, no additional change in holdings are required. This offers potential practical benefits over a cross-sectional strategy from reduced transaction costs to a more practical feasible implementation.

Most academic papers on momentum have not added realism to how actual portfolios are managed. Lewis (2010) argues that actively managed portfolios not necessarily are rebalanced using fixed intervals as we see in the academic literature. Next, for most funds, shorting often has operational issues as well as other efficiency problems, e.g., the sequence of returns related to a positive return bias in stocks. Third, we have limited robustness in methodologies using a certain "look back" period, e.g., 12 months, to determine cross-sectional momentum stocks to short/long and then holding for these for another 12 months. That way, the effect (momentum) is more prone to a sample bias and could statistically speaking hold a relative amount of stocks performing well that is unrelated to the effect wee seek to actual measure. Lewis (2010) thus have constructed a continuous monte-carlo based testing platform attempting to mitigate these deficiencies. This process allowed for rebalancing the cross-sectional portfolio on an "as needed" basis, e.g., daily or weekly (not fixed) to test whether to include (exclude) stocks. This simulation platform also incorporated valid solutions to the problem of small sample (and selection bias)[5] and ended up simulating

[5] Lewis (2010) by randomly selecting for example the top 25 securities from for example a cross section of 100 assets (e.g., top 10% performing stocks) and each day at random sell a stock if it performed below the top half and at random buying a new stock from the top decile of ranks. This selection process is then repeated until the end of the test period.

100 different cross-sectional momentum strategies using the exact same parameters. The authors found that during a 15 year simulation period, all 100 simulations of cross-sectional momentum outperformed the benchmark 100% of the time. The authors concluded that the cross-sectional momentum strategy exhibited extremely robust performance over an intermediate period and weak (underperforming) performance of the very short and long term look back periods (Lewis, 2010).

### 2.3.3 Empirical Momentum at the Oslo Stock Exchange.

Some empirical investigations on the momentum effect at the Oslo stock Exchange (OSE) have been conducted. This section will give a brief overview of central findings in some of these studies. All of these studies have investigated momentum using the Methodology of Jagadeesh and Titman (1993), i.e., cross-sectional momentum forming a market neutral or ”zero cost portfolio”.

Kloster-Jensen (2006) investigated the momentum effect at the OSE using data from 1996 to 2005. All 16 momentum strategies except the j/k = 3/3, yielded significant excess returns. This study found that it was the short positions that was the main driver of returns. The most significant look-back was in this study for j = 6 and 9. For j = 12 a certain decline was noted. By investigating the return profile of the j/k = 3/3, 6/6, 9/9 and 12/12 momentum portfolios compared to the Benchmark, the author made a general remark that the strategies exhibited the best performance during ”bull markets”. Transaction costs was not included. In another study, Myklebust (2007) investigated momentum at the OSE using data from 1984 – 2006. Central findings in this study was that during the entire sample period, the strategies exhibited significant excess returns compared to the benchmark. The j/k = 3/3 strategy had the lowest t-value of 2.64 while the j/k = 6/9 and j/k = 9/9 exhibited substantial significance of t = 7,58. To further indicate the robustness of the results a set of sub-samples was constructed, 1984 – 1989, 1990 – 1994, 1995 – 1999 and 2000 – 2005. All periods except during 1990 to 1994 exhibited significant alpha. The author concluded that the cross-sectional momentum strategy possibly not worked during down markets at the Oslo Stock exchange. The investigation by Myklebust (2007) also did not account for transaction costs. Vas & Absolansen (2014) conducted an empirical investigation of the momentum effect at the Oslo Stock Exchange using 9 year data sample period ranging from 31.12.2004 to 31.12.2013. Significant excess returns could be documented on all j/k look back period. In The short-side of the strategy appeared to be driving the alpha loadings, however, through additional split samples the author speculated that this might be sample period specific and find that during 2005 to 2008 the long side contributed to the excess returns while the contribution during 2009 – 2013 could be contributed to the short side. In accounting for transactions costs the significant alpha disappeared for overlapping holding periods. Non – overlapping holding periods are in practice much less burdened by transaction costs.

### 2.3.4 Momentum rational basis

To this date, no consensus on the possible underlying reasons for the momentum effect have been established (Fama French (2008), Antonacci (2014)). However this subject have been hotly debated and research in the recent years. The studies conducted on explaining the momentum anomaly have not only opened up to many additional questions with regards to market functionality but also contributed a great deal to our general understanding of the markets work, but will also help us be more comfortable or confident in trading-systems based on momentum. We can divide the general models trying to explain momentum into risk based and behavioral based schools of thought. Identifying a risk based explanation for momentum have proven to be very difficult and can not be explained by traditional factor pricing models (Fama & French 1996, Fama & French 2008). Behavioral models attempts to explain the momentum anomaly through certain identified behavioral biases. In general, the few behavioral biases that studies have linked and speculated to attribute to the momentum effect are the same today as they were two decades ago (Antonacci 2014). We can divide the behavior models found in the literature into those that attribute momentum to either an under or overreaction to information. The hypothesis of an underreaction (e.g., Hong, Lim and Stein (2000)) is characterized by a slow diffusion of information through the marketplace. In a behavioral perspective, this slow diffusion can be thought of as consequences of a conservatism bias and the related biases, anchoring and confirmation bias. On the other hand, hypothesis related to an overreaction (e.g., Jagadeesh & Titman 2001)) link overconfidence to the biases of self-attribution and overconfidence.  A recent paper by Haidari (2015) presents evidence in favor of an investor overreaction using idiosyncratic volatility and turnover. This paper confirm that stocks with high idiosyncratic risk (high-uncertainty stocks) are linked to greater momentum profits but also provides the distinction that when investor under-reaction is low, the momentum effects are more due to industry momentum rather than single stocks, while momentum returns when investor overreaction is high can be contributed to a greater extent towards single stocks.

In closing this section, it can be concluded that we have yet to see any consensus on this debate and evidence points to both directions. It is therefore quite possible that the observed inefficiencies related to momentum both can stem from a certain under- and overreaction in the market. Berger, Israel and Moskowitz (2009), argues that such simultaneous inefficiencies, although intuitive, not will cancel each other out but create reinforcement as the observed under and overreaction tend to occur at different points in time. Further, theories like the adaptive market hypothesis indicates that markets both can be rather rational under certain circumstances while also fall prey to collective irrationalism in others. It is therefore not likely that one certain behavioral (or rational explanation for that matter) will close the debate. Nevertheless, research into the momentum effect will undoubtedly continue to give interesting and helpful insights both into the anomaly itself but also the behavior people interacting in the markets and the human psyche.

## 2.4 Financial theory.

Asset pricing is based on discounting future cash flows. Finding an appropriate rate of return to discount these future cash flows with is then an imperative part of valuation. For this, most scholars and practitioners rely on two main procedures: The capital asset pricing model (CAPM) and the arbitrage pricing model (APT) (Berlinger, E. 2015). The CAPM is in essence based on future expected returns (ex-ante), while the rationale behind the APT lies on the no arbitrage principle. This section presents the APT model and then its application to the Fama-French three-factor (FF3), Carhart four factor model (C4F) and empirical factor models in the Norwegian stock market. The chapter concludes with a section on the CAPM[6].

### 2.4.1 The Arbitrage Pricing Model (APT).

The APT model is a linear model constructed on the principle that that asset returns are taught to be a product of their macroeconomic and firm specific risk factors, i.e., systematic and non-systematic risk respectively and is defined as follows

$$r_i = E\left[r_i\right] + \sum_{j=1}^{n} \beta_{ij} F_j + e_i \qquad (1)$$

Equation (1) states that returns of asset $i$, is a function of its expected returns $E[r_r]$

[6] For an in depth discussion on the CAPM and the factor pricing models please refer to e.g., Cochrane (2005), "asset pricing"

, an unexpected change $F_j$ in the $jth$ factor multiplied with the sensitivity asset *i,* has to the $jth$ factor, $\beta_{ij}$. $e_i$ is the residual or "firm specific risk". We have that $E\left[\sum_{j=1}^{n} \beta_{ij} F_j\right] = 0$, ,$E[e_i]$ and $E\left[cov\left(\sum_{j=1}^{n} \beta_{ij} F_j, e_i\right)\right] = 0$, i.e. the random systemic effect and the random firm specific effect both have a zero expected mean and are independent of each other. By adding additional assets to a portfolio the limit of the firm-specific risk approaches zero while no such diversification effect is possible for the systematic risk factor as beta risk affects all components within this asset class. The general APT framework assumes Efficient markets and its underlying implications, e.g., rational investors, a transaction-less and frictionless market (Berlinger 2015). In addition it is assumed that factor mimicking portfolios exist. These portfolios are continuously tradable with a factor exposure (beta value) equal to one for that particular factor and zero for all other factors. We can derive a general pricing formula as follows

$$E\left[r_i\right] = \beta_{i1}\left(r_1 - r_f\right) + \beta_{i2}\left(r_2 - r_f\right) + \ldots + \beta_{ij}\left(r_j - r_f\right) = \sum_j \left(r_j - r_f\right)\beta_j^i \qquad (2)$$

Thus the expected price of an asset $i$ under the APT is a product of the sensitivity to the $j$th risk factor $\beta_{ij}$ multiplied with the risk premium associated with this factor $\left(r_j - r_f\right)$. $r_f$ is the risk free rate. Using the APT in empirical research, we have the following general linear multiple regression equation:

$$\left[r_i - r_f\right] = \alpha_i + \beta_{i1}\left(r_1 - r_f\right) + \ldots + \beta_{ij}\left(r_j - r_f\right) + \varepsilon_i = \alpha_i + \sum_{j=1}^{J} \left(r_i - r_f\right)\beta_j^i + \varepsilon_i \qquad (3)$$

$\alpha_i$ is the constant (alpha) and $\varepsilon_i$ is the firm specific risk component. Using only the market as a relevant factor, i.e., a one factor model, APT and CAPM will coincide. The factors in the APT model must be measured empirically (traditionally using OLS). Related to explaining market anomalies such as the momentum effect using macroeconomic risk factors, a vast body of empirical research find such factors, e.g., inflation, interest etc., unreliable as the operationalization of measuring the fundamental economic effects is subject to significant noise (Næs, R., Skjeltorp, J., & Ødegaard, B. A. (2008)). This can represent a serious problem with a misspecification bias in the regression equations. The Fama-french three factors (FF3), presented in the next sections have proven to have high specificity with regards to the underlying economic relationships we want to measure and have an empirically robust track record in explaining stock returns.

Today it have now become a standard practice to assess the performance of an investment strategy against these and a few other factors (Chong, J., & Phillips, G. M. (2015)) .

### 2.4.2 Fama French three-factor model

In the widely influential paper from Fama and French (1996) it is shown that expected stock returns can be explained by the following time-series regression equation:

$$r_{it} - r_{ft} = \alpha_i + \beta_i\left(r_{mt} - r_{ft}\right) + \beta_i SMB_t + \beta_i HML_t + \varepsilon_{it} \tag{4}$$

The authors here propose that in addition to a broad and well-diversified market portfolio, expected excess return can be explained by (i); the difference between a hedging portfolio long in small-cap stocks and short large-cap stocks (Small Minus Big, SMB) and(ii); and the difference between a hedged portfolio long value-stocks and short growth stocks (High Minus Low, HML). The explicit inclusion of these two factors could now explain a significant portion of returns previously labeled anomalous by the Sharpe and Lintner CAPM model.

### 2.4.3 additional factors and the Carhart four-factor model

However, certain returns still could not fully be explained by the established factors. Especially robust are those accounted for in Fama French (2008), i.e., returns associated with net stock issues, accruals, and momentum. The latter has persistently proved unexplainable by the common risk factors. Carhart (1997) proposes therefore a four factor model consisting of the FF3 factors with an additional momentum factor, PR1YR, constructed to capture the momentum effect based on the methodology of Jagadeesh and Titman (1993). In addition to the momentum factor PR1YR; introduced by Carhart (1997), it is also common practice to augment the three-factor model with a liquidity factor (LIQ) as a relevant explanatory variable (Fama French 2015).

### 2.4.4 Empirical research on factor models at the Oslo Stock Exchange.

In the Norwegian stock market, Næs et al (2008) carried out an empirical investigation of the systematic risk factors affecting the Oslo Stock Exchange (OSE). One of the main findings in this study is that a representative market portfolio, a size factor and a liquidity factor are a reasonable fit for explaining returns on the OSE. Consequently, they found that using the PR1YR factor, only weak evidence for a momentum effect could be documented in the Norwegian stock market. Using data from 1991 to 2010, Korneliussen & Rasmussen (2014), found a four factor model containing the market factor, size-factor, book-to market factor and a momentum factor to be a reasonable model in explaining the cross-sectional returns at the OSE.

$$r_{it} - r_{ft} = \alpha_i + \beta_i \left( r_{mt} - r_{ft} \right) + \beta_i SMB_t + \beta_i HML_t + \beta_i MOM_t + \varepsilon_{it} \quad (5)$$

### 2.4.5 The capital asset pricing model (CAPM)

Harry Markowitz (1952) developed a groundbreaking mathematical optimization algorithm that could construct portfolios with the highest risk adjusted returns in a given universe of securities. This optimization technique was called mean – variance optimization. In its traditional sense, the MVO uses the expected future returns and covariance's between each asset. This procedure however is very unstable given both the sensitivity with regards to the inputs and estimating expected future returns. Although ingenious in theory, the MVO procedure have not proven to be a very practical tool, often resulting in extreme output weights and other faulty maximization portfolios. Calculating a covariance matrix for a larger number of securities was also around the 1950 to 1960s a highly demanding and often impractical task. Thus, in the mid 1950s, a set of researcher started to develop alternatives with a more theoretical, intuitive and simplified inputs. Thus, the CAPM came about as a result of the simultaneous independent work of three scholars, William Sharpe, John Lintner, Jon Mossin and later Fischer Black (Fox, 2009).

In essence the CAPM is a simple regression of an assets (or portfolio) excess return and the market index. Thus, the beta coefficient from the resulting estimate is the sensitivity of that asset to variation in the market portfolio, i.e., how much movements in the aggregate market index contributes to movements in the asset (portfolio). We can thus formulate the expected return on asset *i* as:

$$E\left[ r_i \right] = r_f + \beta_i \left( E\left( r_m \right) - r_f \right) \quad (6)$$

Here, $r_f$ is the risk free rate, $\beta_i$ is the asset sensitivity to the market index/portfolio. The theory is based on a stylized universe consisting of a uniform set of rational mean variance optimizing risk averse investors all using the MVO as their optimal portfolio criteria in a one-period universe. The aggregate equilibrium is then in the mean-variance efficient portfolio. The CAPM relies heavily on the assumptions of the efficient market hypothesis and as discussed closely related to the work by Fama (1970). Consequently investors have homogenous belief's about risk and reward, a widely available risk free rate for borrowing and lending at the same rate, no taxes, transaction costs or other market frictions, each investor is a price taker unavailable to affect aggregate prices (Bodie 2009, p.264) In addition normal, serially independent and static time-variance of the return distribution are assumed[7].

We can interpret the CAPM in an empirical setting as a special case of equation (3) where the market portfolio is the only relevant risk factor. In light of this simple regression equation we can gauge performance based on the alpha, beta and t-statistics. If relying on the CAPM we can beat the market by taking on additional market risk (beta), i.e., a know risk factor and/or outsmarting relative to other investors (alpha). The realization that CAPM did not hold up too well in empirical investigations led to (amongst others improvements) the FF3 model. Financial theory Summary

Despite theoretical limitations and simplifying assumptions, the linear models presented in this chapter have shown predictive power in indicating asset(portfolio) returns in relation to risk. As is now routinely used in assessing the statistical significance and performance of investment returns, the momentum investigations at the OSE in this thesis will be regressed against a multifactor model detailed in chapter 3.

## 2.5 Portfolio performance measures

One of the ways in which I will demonstrate and evaluate the ex-post performance of the constructed portfolios is through the calculation of a set of performance measures, both across the entire sample period and set of sub-sample periods. For this task, it is a common practice to use the Sharpe Ratio and other simple variants utilizing the first and second moments around the mean.

> *"Investors do not dislike variability per se. Rather, they dislike losses but are quite happy to receive unexpected gains. Downside risk may be a better reflection of investor´s attitude toward risk" (Simons, 1998, 35)*

Recognizing that no single measure alone is sufficient in analyzing the nuances of portfolio returns and that these simple statistical measures could be improved, I will in addition calculate portfolio performance relative to a set of measures using third, fourth and the lower/upper partial moments of the underlying distribution of returns.

[7] This theoretical assumption have not held up in empirical studies. Stock returns have fatter tails with unstable variance. See for example Mandelbrot (2004)

### 2.5.1 The Sharpe Ratio

The Sharpe ratio is a widely used statistic that seeks to quantify the return per unit of *total,* risk undertaken. This statistic is based on the foundational assumption in modern portfolio theory that the underlying distribution of returns is normal (Bacon, C, 2013), i.e., assuming the third and fourth moments is zero. The Sharpe Ratio is defined as follows:

$$SP_i = \left(\bar{R}_i - R_f\right) \Big/ \sqrt{\tilde{\sigma}^2} \tag{7}$$

Empirically, stocks often exhibit significant Skewness and kurtosis. Looking at equation (7), both positive and negative deviations from the mean are penalized equally, potentially creating misleading conclusions. Thus, in order to present a more comprehensive measure of portfolio performance, I will utilize performance measures that accounts for the preference of upside rather than downside volatility.

### 2.5.2 Partial moment measures.

In the partial moment measures, we capture the *relevant* risk by measuring the *lower partial moments* (LPM), i.e., the variability below an investor specific minimally accepted rate of return, and the upper partial moments (UPM), that is the variability above an investor specific minimally accepted rate of return. In contrast to the Sharpe ratio, the following performance measures presented, treats upside risk as preferred while penalizing the downside, e.g., a distribution of returns with a long right tail or positive Skewness, is now accounted. These measures fall under the category of partial (one-sided) moment measures (see e.g., Bacon (2004), Sortino & Satchell (2001), Sortino (2010)). for and quantified. The first two of the partial-moment performance measures is the Omega and Sortino Ratio.

***The Omega ratio***

The Omega measure is calculated as :

$$\Omega\left(\tau\right) = \int_{\tau}^{\infty}\left[1 - F(R)\right]dR \Big/ \int_{-\infty}^{\tau} F(R)dR \tag{8}$$

Here, the numerator captures the upside by taking the integral of the cumulative distribution function (cdf) of returns, $F(R)$, bounded in the lower plane by the minimally accepted return $\tau$ .The denumerator captures unpreffered risk by taking the integral of the cdf with an upper bound of $\tau$ . Thus, the Omega captures the ratio of upside versus downside risk, *relative* to the investor-specific threshold $\tau$ .

***The Sortino Ratio***

The second LPM measure, the Sortino Ratio is calculated by the following expression:

$$S = \mu - \tau \Big/ \sqrt{\int_{-\infty}^{\tau} \left(\tau - R_i\right)^2 dF(R_i)} \tag{9}$$

Where $\mu = \int_{-\infty}^{\infty} R dF(R)$, is the expected period return, the Sortino ratio is an extension of the Sharpe ratio in that it only uses downside deviation rather than standard deviation in the denominator.

***Kappa 3***

In (Kaplan & Knowles, 2004), it is shown that Omega and Sortino ratio, although apparently distinct, both represent single cases of a generalized risk measure Kappa[8]. The Kappa 3 ratio is defined as follows:

$$K_3\left(\tau\right) = \mu - \tau \Big/ \sqrt[3]{LPM_n\left(\tau\right)} \tag{10}$$

***The Upside Potential Ratio***

The last of the LPM measures used in this thesis is the Upside Potential Ratio, this measure was proposed as a further improvement to the Sortino ratio and is calculated as the first order UPM to the square root of the second LPM relative to the threshold level.

$$Up = \int_{t}^{\infty} \left(R_{i,t} - \tau\right)^1 d\mathrm{F}\left(R\right) \Big/ \int_{-\infty}^{\tau} \left(\tau - R_{i,t}\right)^2 d\mathrm{F}\left(R\right) \tag{11}$$

As in the case of the Omega, Sortino And kappa 3 ratio, negative returns in the $Up$ ratio are measured by LPMs but in the numerator we have the expected value of positive returns instead of the return excess of the threshold level.

Of the other measures presented is the information ratio. This statistic is measured *relative* to a predetermined benchmark. Analogous to the absolute return per unit of absolute risk we have in the Sharpe Measure, the Information ratio evaluates the excess returns of

8 If we define the general N$th$ LPM in continuous form as: $LPM_{\tau-}^{n}\left(R_{i,t}\right) = \int_{-\infty}^{\tau} \left(\tau - R_{i,t}\right)^n d\mathrm{F}\left(R\right)$. Similarily, the N$th$ upper partial moment (UPM) is defined as: $LPM_{\tau+}^{n}\left(R_{i,t}\right) = \int_{t}^{\infty} \left(R_{i,t} - \tau\right)^n d\mathrm{F}\left(R\right)$. Now, using the generalized form, the Omega becomes $\Omega\left(\tau\right) = K_1 + 1$ and Sortino ratio $SoR = K_2 = \mu - R \Big/ \sqrt[2]{LPM_2}\left(\tau\right)$ . Although we can use any $n >= 0$ , I will limit the performance analysis to $n = 1, 2, 3$ , as this appears to be the most frequent application in practice(kappa3).

stock/portfolio $i$ over the benchmark, relative to the standard deviation of these excess returns, i.e., the tracking-error[9]. The information ratio is defined as:

### 2.5.3 The Information Ratio

Let $r_{pt}$ bet the return of an active portfolio at time *t* and the excess return on this portfolio relative to the benchmark $er_t = er_{pt} - er_{bt}$. We define the arithmetic average excess returns from t=1 to T as $\overline{er} = \frac{1}{T}\sum_{t=1}^{T} er_t$. We define the standard deviation of the excess returns as $\hat{\sigma}_{er} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(er_t - \overline{er})^2}$. This latter expression is  also called "the tracking error". The Information ratio is now the ratio return – standard deviation and defined as:

$$IR = \frac{\overline{er}}{\hat{\sigma}_{er}} \tag{12}$$

Expression (12) in essence is the average excess return per unit of excess return volatility (Goodwin, 1998) and can be interpreted as the portfolio managers skill/quality in relation to the risk of this information. A positive information ratio is an indication that the portfolio in question have outperformed the benchmark.

# 3. Data

## 3.1 Presentation and filtering

The basic data in this paper are obtained from Thomson Reuters Datastream and consists of monthly prices, market capitalization, trading volume (turnover) and sector classification on all equities traded at the Oslo stock exchange from January 1980 to December 2015 (unless otherwise noted). Two different sets of price series are used: One set of unadjusted prices - prices is as it were historically obtained from the exchange while the other set are series adjusted for all dividends, interest, rights offerings and all other distributions that might affect the investor over time, i.e., a total return index. The former is only used for filtering stocks while the latter is used in all calculations, e.g., back testing returns. The total return index assumes a reinvestment of dividends and stock distributions back into the same stock as they originated, thus creating a more realistic picture of the actual stock performance. Not accounting for distributions would create spurious performance rankings between stocks, e.g., stocks paying dividends would be ranked relatively worse compared to non-paying companies (Clenow, 2014)

DataStream provided for a certain portion of the sector classification but since the OSE initiated the Gics[10] standard in 1997, a significant amount of this information was filled manually.

Some of the stocks traded at the Oslo stock Exchange have a low turnover. Illiquid stocks are a source of noise that adversely affects certain empirical asset investigations (Ødegaard, 2016). Stocks are therefore required to have a monthly transaction volume > 10,000. Following the same rationale, the impact of exaggerated returns for low value stocks are minimized by requiring the stock to have a price above NOK 10 and Market value above NOK 10 million before considered in the sample calculations. This filtering criteria is

[10] The Global Industry Classification Standard (Gics) swas developed by standard & poor as an efficient investment tool for capturing industry sectors. For more information I refer to: https://www.msci.com/gics

applied to all constructed portfolios and calculations in the following chapters. In summary the following each stock must fulfill the following requirements in order to enter the sample:

- Have had more than 10,000 transactions the month..
- An Unadjusted price of at least NOK 10
- And a Market capitalization of at least NOK 10 million

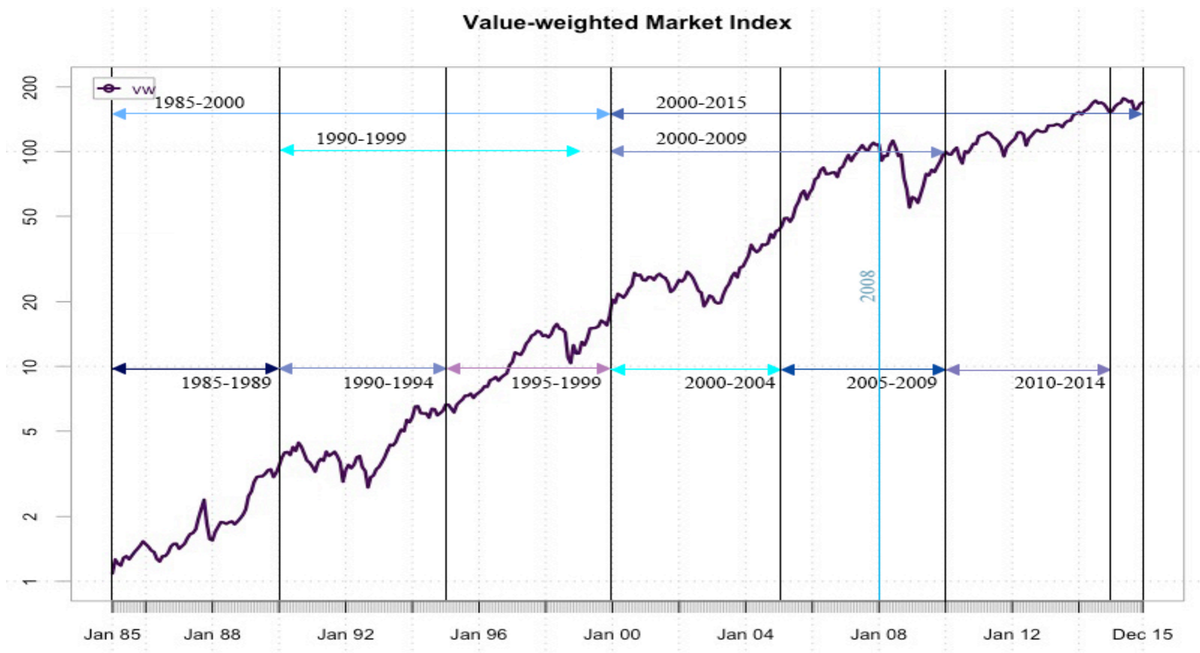
See appendix A for of an overview of stocks excluded.

### 3.1.1 Risk Free Rate and Market risk factors

The 1-month NIBOR is used for calculating returns in excess of the risk-free rate. For this interbank rate, monthly data are readily available from 1986[11]. During 1985 the proxy of overnight NIBOR accounted for in Ødegaard (2016) will be used. The Monthly Risk free rate, Fama-French and the Carhart market factors are gathered from Bernt Arne Ødegaard´s website.[12] All factor time-series use simple returns and the data series starts from July 1981.

### 3.1.2 Sample periods

***Figure 1: Sub-Sample periods***




[11] Norges Bank...

[12] Please refer to: http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html

## 3.2 Statistical software

All computations are conducted in R v 3.2.4.

# 4. Methods

## 4.1 Portfolio Construction

### 4.1.1 Market portfolios

After filtering, all remaining stocks are used to calculate both equal and value-weighted benchmark/index portfolios (see section 3.1 and Appendix for code). The equally-weighted portfolio is calculated as follows:

$$r_{mkt}^{ew} = \sum_{i=1}^{N} r_{i,t} \tag{13}$$

Here, each month, the total return $r_{mkt}^{ew}$ is the average of the simple returns of each asset $i$ at time $t$. In practical terms, this implies equal money allocation to each stock. The Value-weighted portfolio returns are weighted according to its fraction of the total market value and defined as follows:

$$r_{mkt,t}^{vw} = \sum_{i=1}^{N} w_{i,t} r_{i,t}, \qquad w_{i,t} = \frac{Mv_{i,t}}{\sum_{i}^{N} Mv_{i,t}} \tag{14}$$

Where the weight of asset $i$ at time $t$, are the fraction of its market value over the sum total of the market value of all assets under consideration at time $t$. This implies that funds are allocated according to the relative value of the stock at that particular time. The equal and value weighted market portfolios will serve both as a benchmark relative to other portfolio strategies and as an indicator of time-series momentum.

### 4.1.2 Sector portfolios

***Table 1: GICS Classification***

| Code | Sector | Industry Groups |
|---|---|---|
| 10 | Energy | Energy |
| 15 | Materials | Materials |
| 20 | Industrials | Capital Goods, Commercial & Professional Services, Transportation |
| 25 | Consumer Discretionary | Automobiles & Components, Consumer Durables & Apparel, Consumer Services, Media, Retailing |
| 30 | Consumer Staples | Food & Staples Retailing, Food, Beverage & Tobacco, Household & Personal Products |
| 35 | Health Care | Health Care Equipment & Services, Pharmaceuticals, Biotechnology & Life Sciences |
| 40 | Financials | Banks, Diversified Financials, Insurance, Real Estate |
| 45 | Information Technology | Software & Services, Technology Hardware & Equipment, Semiconductors & Semiconductor Equipment |
| 50 | Telecommunication Services | Telecommunication Services |
| 55 | Utilities | Utilities |

According to their respective GICS classification, all stocks are distributed into a set of 10 different sector portfolios. The aggregate returns for each of these portfolios are then constructed using both equal and value weighted calculations, resulting in 10 equally and 10 value-weighted buy & hold (B&H) sector portfolios.

### 4.1.3 Cross-Sectional momentum strategies

Each month, the arithmetic rate of change (ROC) for each stock over the prior $j$ months are calculated as follows

$$r_{i,t-j-1} = \frac{P_{i,t-1} - P_{i,t-1-j}}{P_{i,t-1-j}}, \qquad j = \{3, 6, 9, 12, 16\} \tag{1.15}$$

Where $j$ is the “look – back” period and $r_{i,t-1-1}$ is the ROC on stock $i$ over at time $t$ Each month all stocks are ranked and assigned into ten decile portfolios according to their respective ROC for all $j$ look-back periods, thus we have the top performing 10% of stocks in the top (winners) portfolio all the way to the bottom 10% (losers). A total of ten different cross-sectional stock momentum(XSI-MOM) portfolios, $P1, P2, \ldots, P10$ are constructed by taking a long (buy) position in each stock contained in the different deciles.

Similarly, a set of cross-sectional sector momentum (XSS-MOM) portfolios are constructed for each sector $i$ in principle using the same methodology and described above: XSS-MOM, is applied by sorting sectors according to the appropriate decile interval in which each sector fall based on the performance over the preceding j months relative to the performance of the other sectors in the cross-section. Since we most of the time have 10 sectors, each decile portfolio P1 – P10 generally holds one sector during most periods. However it is important to keep in mind that, during the period 1985-1996, we only have 8 sectors and hence the same sector can exist in two different portfolios.

For both the XSI-MOM and XSS-MOM, equal and value –weighted portfolios are constructed, See table 3 below for an overview of the total number of constructed portfolios.

### 4.1.4 Time-series momentum (trend-following) overlay.

A time-series (trend following) dynamic(hedge) overlay (TSF) is constructed using the value-weighted benchmark (index) portfolio $r_{mkt}^{vw}$, for $j^* = \{3, 6, 9, 12, 16\}$ look-back periods. The TSF is a proxy for determining if the asset class in question (in this case stocks) are in an aggregate positive or negative momentum[13]. The TSF is computed as follows:

$$TSF = \prod_{t-j^*-1}^{t-1} r_{it,mkt}^{vw} - \prod_{t-j^*-1}^{t-1} r_{t,rf}^{N3M} \tag{16}$$

each month, the rolling cumulative return for the value-weighted (vw) market portfolio (index) less the rolling cumulative return for the risk free rate (N3M: 3-Month overnight NIBOR) are calculated. The dynamic time-series overlay is applied to each constructed portfolio by seeing if the cumulative return of the vw-benchmark less the risk cumulative return of the risk free rate (N3M) has been in a positive or negative trend over the $j$ preceding months.

$$\text{Time-Series Overlay} = \left\{ \begin{array}{ll} \text{Stay in Portfolio Position} & \text{if TSF} > 0 \\ \text{Enter Fixed Income (N3M)} & \text{if TSF} < 0 \end{array} \right\}$$

If TSF is positive, the overall (absolute) momentum in stocks is expected to be in an upwards trend and we therefore stay invested in the portfolio. If TSF is negative, stocks are expected to be in a downward trend and we then leave the portfolio position and enter fixed

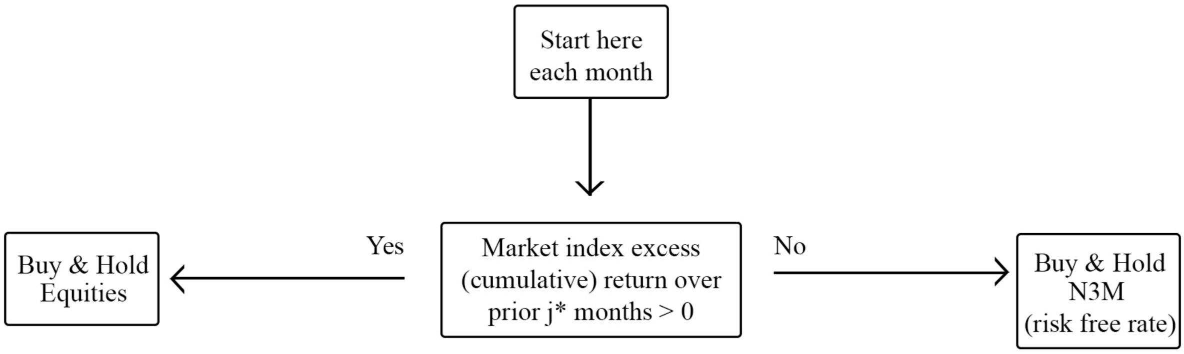
[13] We could have used the same time-series momentum applied to each stock but due to the high correlation between stocks, the broad market index can serve as a reasonable proxy. For examples of this relatively novel(from an academic structured research perspective) implementation of momentum, I refer to e.g., Faber (2010) or Antonacci (2013, 2014).

income until TSF again turns positive. Portfolios consisting of a combination of cross-sectional momentum with a time-series overlay is called Dual-Momentum stock (DMI*j*j*) momentum and Dual-Momentum sector (DMS*j*j*) momentum portfolios. See table 1 below for an overview of the total number of Dual momentum, benchmark portfolios with a time-series overlay (TS*j**), and sector portfolios with a time series overlay (TSS*j).*

### 4.1.5 Portfolio construction overview

***Figure 2: Time-Series momentum.***

Figure 2 illustrates the basic process of the time-series overlay.



## *Table 2: Portfolio construction Overview*

Table 2 Gives an overview of the total number of constructed portfolios

**Panel A: Total Number of Cross-sectional momentum portfolios constructed**

Each row in column 1 lists the different j look-back periods (months) used in constructing the respective portfolios. Column 2 and 4 summarizes the total number of cross-sectional stock momentum portfolios constructed using all j = 3, 6, 9, 12 and 16 month look-back periods. Column 3 and 5 summarizes the total number of cross-sectional sector momentum portfolios constructed using all j = 3, 6, 9, 12 and 16 month look-back periods. A total of 100 Cross-sectional stock momentum portfolios (XSI-MOM) and 100 Cross-sectional sector momentum portfolios (XSS-MOM) are constructed. This gives a total of 200 Cross-Sectional portfolios.

| Look-back | Value-weighted | | Equally-weighted | | |
|---|---|---|---|---|---|
| j ( months) | XSI-MOM | XSS-MOM | XSI-MOM | XSS-MOM | Sum |
| *3* | 10 | 10 | 10 | 10 | |
| *6* | 10 | 10 | 10 | 10 | |
| *9* | 10 | 10 | 10 | 10 | |
| *12* | 10 | 10 | 10 | 10 | |
| *16* | 10 | 10 | 10 | 10 | |
| Sum | 50 | 50 | 50 | 50 | **200** |

**Panel B: Total Number of Dual -Momentum portfolios constructed**

Column 1 indicates which look-back period $j*$ the TSF layer is based upon. Column 2 indicates which look back period $j$ is used on the respective XSI and XSS portfolios. Thus. Having a total 10 decile portfolios for each $j$ cross-sectional portfolie where there are five different j and five different $j*$, *a total of* $5*5*10*4=1000$ different Dual momentum portfolios is constructed.

| TSF | Cross-Sectional | Value-weighted | | Equally-weighted | | |
|---|---|---|---|---|---|---|
| Look back j* | Look-back j | DMI | DMI | DMS | DMS | SUM |
| 3 | 3 | 10 | 10 | 10 | 10 | |
| 3 | 6 | 10 | 10 | 10 | 10 | |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | |
| 3 | 16 | 10 | 10 | 10 | 10 | |
| 6 | 3 | 10 | 10 | 10 | 10 | |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | |
| 6 | 16 | 10 | 10 | 10 | 10 | |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | |
| 16 | 16 | 10 | 10 | 10 | 10 | |
| Sum | | 250 | 250 | 250 | 250 | **1000** |

**Panel C: Total Number of applied time-series sector portfolios constructed**

Table 3 indicates the total number of Sector portfolios with Applied time Series momentum (TSS$j*$)

| TSF | | | | | Value-Weighted | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| j* | Enrg | Mat | Ind2e | CnsD | CnsS | Hlth | Fin | IT | Tele | Util | Sum |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | |
| 16 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| Sum | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 50 |
| | | | | | Equally-Weighted | | | | | | |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | |
| 16 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | |
| Sum | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 50 |
| | | | | | | | | | | | **100** |

**Panel D: Total Number of Benchmark-portfolios with applied time-series momentum**

| Market - | TSF | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | j*-) | 3 | 6 | 9 | 12 | 16 | Sum |
| vw | | 1 | 1 | 1 | 1 | 1 | 5 |
| ew | | 1 | 1 | 1 | 1 | 1 | 5 |
| Sum | | 2 | 2 | 2 | 2 | 2 | **10** |

### 4.1.6 Performance Measures

Let $R_{i,t}$ be the return of stock $i$ at time $t$, the performance measures discussed is then estimated by treating each sample observation in the dataset as a point in a discrete distribution. For the partial moment measures, The $\mathrm{N}th$ LPM in discrete form is then:

$$LPM_n\left(\tau\right)=\frac{1}{T}\sum_{t=1}^{T}\max\left[\tau-R_t,0\right]^n \tag{17}$$

This discrete implementation enables us to calculate the Omega, Sortino, Kappa 3 and Upside Potential ratio. As a major part of all the constructed portfolios is based on the calculation of the Time-Series momentum presented in section 3.3, we frequently have extended periods of time where observations fall on the fixed (risk free) rate of return. Defining the threshold (minimally accepted return) $\tau$, at or below the risk free rate, would for certain sub-periods potentially create a situation with very few or no observations less or above this threshold. In order to mitigate this pitfall, the threshold level for all portfolios is set to zero, i.e., $\tau = 0$.

For all sub-periods of shorter duration than ten years, the Partial – moment measures must be interpreted with caution as there might not be sufficient returns for some of the performance measures to give meaningful results. In addition to the relative performance of each constructed portfolio strategy, I consider the constructed vale-weighted market portfolio $r_{Mkt,t}^{vw}$, presented in section 3.2, as the relative performance benchmark.

### 4.1.7 Factor regression

The portfolios in this thesis are regressed against the value-weighted market portfolio (see section 2.2) and the SMB, HML, PR1YR and (LIQ) factors accounted for in Ødegaard (2015). I end up with the following time-series regression model:

$$R_{it}-R_{Ft}=\alpha_i+b_i(R_{VW,t}-R_{Ft})+s_iSMB_t+h_iHML_t+p_iPR1YR_t+l_iLIQ_t+e_{it} \tag{18}$$

Where $e_{it}$ is a zero mean residual and the pricing error $\alpha_i$ is the variation in returns not captured by the model.

# 5. Results

This section will present the results from this empirical investigation at the Oslo Stock Exchange. The results have four main parts: The first part, section 5.1 presents the results from the long-only cross-sectional individual stocks and sector momentum portfolios. The second, section 5.2, presents the results of the applied time-series momentum on the market portfolios and sector portfolios (section 5.2.1 and 5.2.2) and combined time-series and cross-sectional momentum - dual-momentum (section 5.2.3). Part three, section 5.3, show the results from the regression analysis on the constructed portfolios. The last part, section 5.4: "comparative analysis", presents and compares the most significant findings from the preceding sections. Unless otherwise noted, the presented portfolios are value-weighted rather than equal weighted portfolios.

## 5.1 Cross-Sectional momentum

Figure 3a, illustrates that only the return profile of portfolio P1 appear to be outperforming (substantially) the benchmark albeit at the expense of additional volatility). The sector portfolios in figure 3c, illustrates that P1, P2 and P3 outperform the benchmark albeit to a much lesser extent than XSI-MOM P1 from figure 3a. Figure 3b (Figure 3d), presents the results of individual stocks (sectors) for P1 using a set of different look-back periods. From Fig 3b and Fig 3d, we see the robust performance of both XSI-MOM and XSS-MOM using different the look-back periods. For the former j = 12 and 9 gives the best result while latter appears to respond best to j = 6 and 16 month look-back periods. From Fig 3b (XSI-MOM) we see that the shorter j = 3 and the longest j = 16 month look back periods exhibit the worst performance, however this is not the case in fig 3d (XSS-MOM). We can further note that for all cross-sectional stock portfolios in Fig 3b and 3d, the increased return profile comes with an increase in in volatility and overall drawdown profile relative to the benchmark. The link between momentum and volatility is further illustrated in Table 5 and Table 6 — the prior best performing and worst performing portfolios over j = 12, overall have a higher standard deviation.

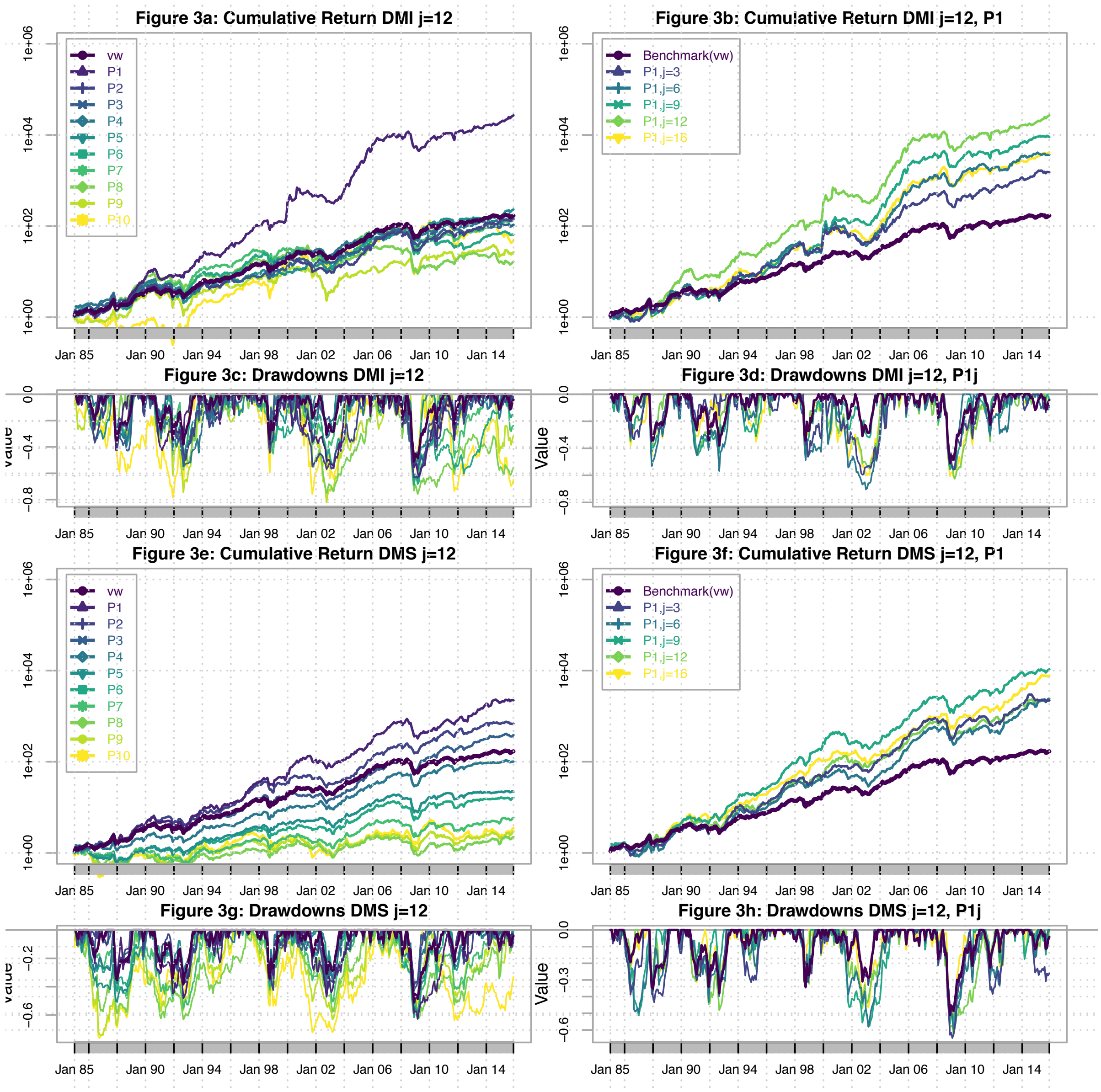
Figure 4 illustrate the robustness of cross-sectional momentum over time and using varying look-back periods. From Figure 4a, XSI-MOM P1, outperform (higher median value) both across all look-back periods and against all other constructed decile portfolios. For P1 we observe the robustness of Cross-Sectional momentum with the continued strength using different look-back periods. We note the strongly positive outlier (right tailed event) for j = 12. For P2, the (median) Sharpe ratio outperforms all $\text{Portfolios} \neq \text{P1}$ using j = 3 and 6, however this pattern does appear to hold for j = 9, 12 and 16. From Fig4b, we see that during the sample periods 1985 - 2015, 2000 – 2015, 1990 – 1999 and 2000 – 2009, P1 outperform all portfolios and benchmark using over all look-back periods. During 1990 – 1999 P1 generally performs equal to or (in the case for j = 12) better than benchmark and all other portfolios. The performance of the cross-sectional individual stock (XSI-MOM) portfolios during the financial crisis (2008) is erratic, highly volatile and poorly performing. Fig 4c show XSI-MOM performance during five-year sub-sample periods. For P1, j = 12 outperforms benchmark during all periods, j = 6,9 and 16 outperforms benchmark on five out of six five-year periods and j = 3 outperforms on three out of six periods. Thus, we note the better performance over the long term relative to the five-year periods.

From Figure4c, d and e, XSS-MOM P1, generally yield a better performance than all other portfolios over the prior j months. The distance between P1 and P2 is distinctly less pronounced for XSS-MOM than XSI-MOM, indicating it a viable strategy to trade the top one to three (and even four) top-performing sectors over the prior j months. Fig 4c,d, and e (XSS-MOM) indicate an inverted or slightly convex relationship of Outperformance from P1 to P10. This relationship however is not as clear or prevalent for the XSI-MOM portfolios. From Fig4d and e see a more predictable pattern of performance from high prior returns (P1) to low (P10), relative to the XSI-MOM strategies in Fig 4a and b. Neither XSI-MOM nor XSS-MOM is profitable during the financial crisis and mostly at par with the general market. Long-Only Cross-sectional momentum therefore does not appear profitable during recessions (the financial crisis). Table 3 show the Performance measures for the XSI-MOM strategies using a j = 12 month look-back period over twelve different sample periods. Overall we note a striking over-performance from the P1 portfolio on all return and risk-adjusted performance measures throughout all periods except the financial crisis (2008). For P1 we see a positive information-ratio, indicating outperformance over the Benchmark (vw). Although relatively volatile compared to P2-9, portfolio P1 systematically exhibits significant positive Skewness (upside volatility), resulting in lower (worst) drawdowns across the sample periods and a substantially higher cumulative return profile. The positive skew of P1 makes the argument for using performance measures based on the lower partial moments instead of the Sharpe-ratio in gauging actual investment performance. From table

3, P1-P3 (P4) XSS-MOM strategies overall over-perform relative to P5-P10. We see a pattern of positive information-ratio values for P1, P2, P3 and (less) P4 indicating out-performance relative to the benchmark.

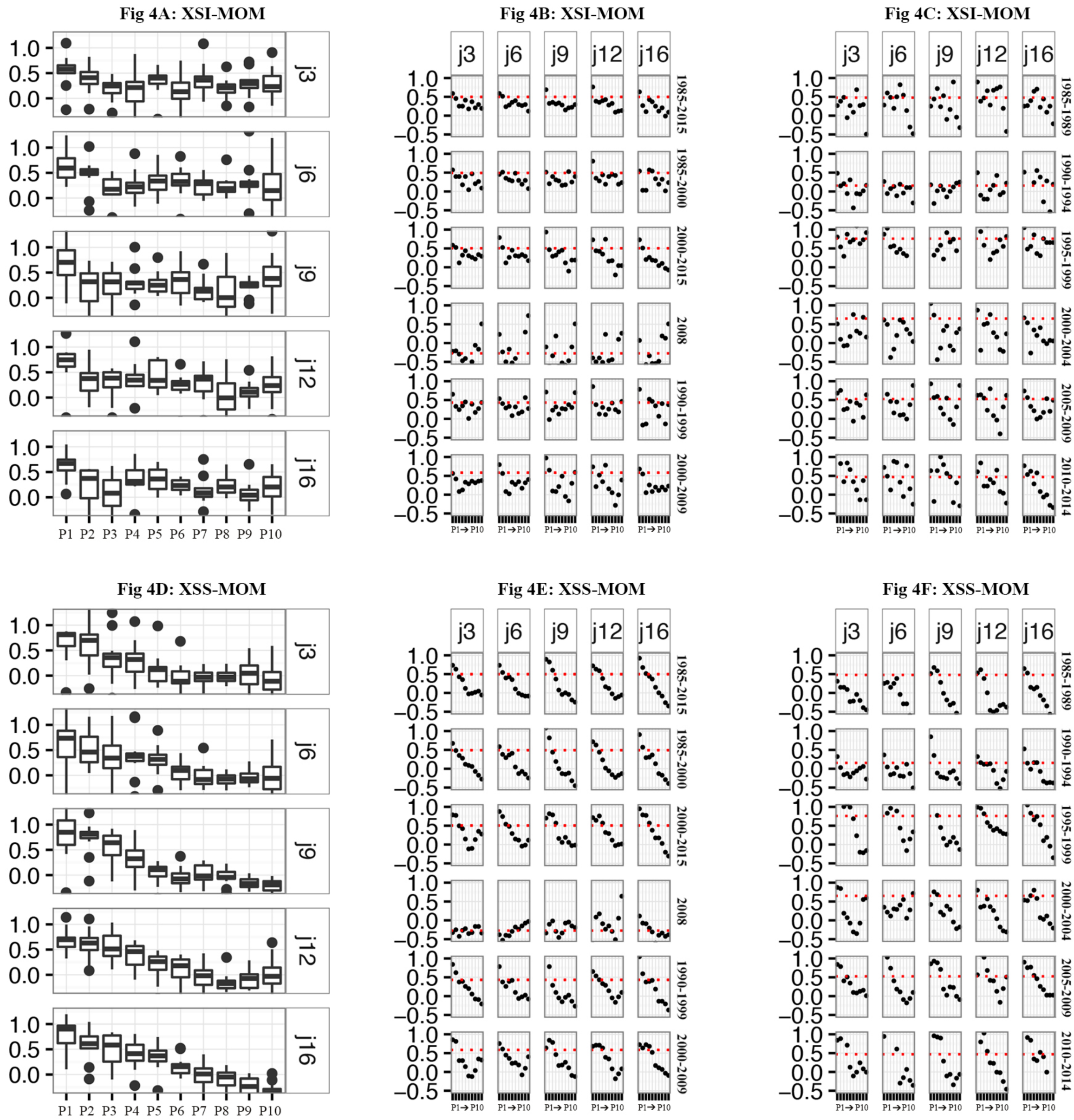
***Figure 3: Cross-Sectional Momentum Cumulative Returns and Drawdowns:***

Fig 3a and 3c (3e and 3g) show the cumulative log returns and drawdowns for the XSI-MOM (XSS-MOM) decile portfolios using a j = 12 month look-back period. Fig 3b and 3d (3f and 3h) show the cumulative log returns and drawdowns for XSI-MOM (XSS-MOM) P1 using a set of different look-back periods.



### *Figure 4: Robustness tests*

Fig 4a (4d) show the Sharpe-ratio for the each XSI-MOM (XSS-MOM) P1-P10 using a set of different look back periods from j = 3,6,9,12,16. Each boxplot contains statistical information for the Sharpe ratio over the entire sample period as well as all sub-sample periods, i.e., a total of n =12 observations, described in section 3.1.2. Outliers are represented with dots outside the box. Fig 4b (4e) show the Sharpe-ratio pattern for the each XSI-MOM (XSS-MOM) P1-P10 using a set of different look back periods from j = 3,6,9,12,16 during the sample periods 1985-2015, 1985 – 2000, 2000-2015, 2008 (the financial crisis), 1990-1999 and 2000 – 2009 Fig 4c (4f) show the Sharpe-ratio pattern for the each XSI-MOM (XSS-MOM) P1-P10 using a set of different look back periods from j = 3,6,9,12,16 during a set of five-year sample periods 1985-1989, 1990 – 1994, 1995 – 1999, 2000 – 2004, 2005 – 2009, 2010 – 2014. The dotted line represents the Sharpe-Ratio of the benchmark (vw-portfolio)



### *Table 3: Performance Measures Cross-Sectional Individual Stock Momentum.*

This table shows the performance measures and descriptive statistics for all XSI-MOM decile portfolios P1 to P10 using a j = 12 month-look back period. Panel B-E show a set of longer sub-sample periods in addition to 2008 the financial crisis in Panel F. Panel G-L show a set of five-year sub-sample periods.

| J=12 | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Panel A: 1985 - 2015*** | | | | | | | | | | ***Panel D: 1990 - 1999*** | | | | | | | | | |
| *Up Pot* | 1.09 | 0.76 | 0.78 | 0.82 | 0.87 | 0.71 | 0.72 | 0.67 | 0.68 | 0.73 | 1.11 | 0.81 | 0.68 | 0.75 | 0.75 | 0.75 | 0.78 | 0.74 | 0.73 | 0.93 |
| *Inf Ratio* | 0.71 | -0.04 | -0.10 | -0.05 | 0.07 | -0.22 | -0.10 | -0.45 | -0.25 | -0.12 | 0.89 | 0.01 | -0.42 | -0.15 | -0.45 | -0.20 | 0.21 | -0.16 | -0.07 | 0.38 |
| *Omega* | 1.49 | 0.77 | 0.73 | 0.80 | 0.82 | 0.64 | 0.70 | 0.41 | 0.47 | 0.48 | 1.54 | 0.81 | 0.52 | 0.72 | 0.47 | 0.63 | 0.89 | 0.64 | 0.60 | 0.96 |
| *Sortino* | 0.65 | 0.33 | 0.33 | 0.36 | 0.39 | 0.28 | 0.30 | 0.20 | 0.22 | 0.24 | 0.67 | 0.36 | 0.23 | 0.31 | 0.24 | 0.29 | 0.36 | 0.29 | 0.27 | 0.45 |
| *Kappa3* | 0.45 | 0.22 | 0.23 | 0.25 | 0.27 | 0.18 | 0.19 | 0.13 | 0.15 | 0.17 | 0.46 | 0.23 | 0.16 | 0.22 | 0.17 | 0.20 | 0.24 | 0.20 | 0.18 | 0.33 |
| *Sharpe* | 0.76 | 0.39 | 0.34 | 0.39 | 0.43 | 0.27 | 0.31 | 0.09 | 0.12 | 0.13 | 0.86 | 0.38 | 0.12 | 0.29 | 0.12 | 0.26 | 0.42 | 0.24 | 0.19 | 0.46 |
| *Std. dev* | 0.4 | 0.26 | 0.26 | 0.26 | 0.28 | 0.27 | 0.29 | 0.31 | 0.37 | 0.48 | 0.32 | 0.26 | 0.26 | 0.26 | 0.28 | 0.27 | 0.32 | 0.31 | 0.41 | 0.52 |
| *Annual R* | 0.39 | 0.174 | 0.163 | 0.173 | 0.192 | 0.144 | 0.162 | 0.095 | 0.112 | 0.134 | 0.37 | 0.19 | 0.11 | 0.16 | 0.11 | 0.15 | 0.22 | 0.16 | 0.16 | 0.33 |
| *Cum Ret* | 26892 | 144 | 107 | 140 | 231 | 64 | 103 | 16 | 26 | 48 | 23 | 4 | 2 | 3 | 2 | 3 | 6 | 3 | 3 | 17 |
| *W DD* | -62% | -64% | -58% | -57% | -52% | -69% | -67% | -76% | -82% | -78% | -43% | -50% | -55% | -55% | -51% | -46% | -51% | -57% | -74% | -74% |
| *Skew* | 2.7 | -0.6 | 0.0 | 0.2 | 0.3 | -0.6 | -0.5 | -0.3 | 0.0 | 0.3 | 0.4 | -0.5 | -0.6 | -0.3 | -0.1 | -0.6 | -0.4 | -0.2 | 0.1 | 0.8 |
| *Ex Kurt* | 21.2 | 1.7 | 2.0 | 2.1 | 2.0 | 2.5 | 2.6 | 1.2 | 1.8 | 1.3 | 1.1 | 1.9 | 1.5 | 0.9 | 0.6 | 0.6 | 2.0 | 1.4 | 1.9 | 1.7 |
| | ***Panel B: 1985 - 2000*** | | | | | | | | | | ***Panel E: 2000 - 2009*** | | | | | | | | | |
| *Up Pot* | 1.20 | 0.86 | 0.79 | 0.86 | 0.84 | 0.86 | 0.82 | 0.86 | 0.76 | 0.84 | 1.17 | 0.65 | 0.86 | 0.77 | 0.94 | 0.62 | 0.60 | 0.50 | 0.61 | 0.76 |
| *Inf Ratio* | 0.78 | -0.10 | -0.19 | 0.06 | -0.31 | -0.04 | 0.14 | 0.11 | -0.17 | 0.01 | 0.66 | -0.45 | 0.01 | -0.34 | 0.49 | -0.50 | -0.71 | -1.13 | -0.46 | 0.14 |
| *Omega* | 1.84 | 0.82 | 0.80 | 1.02 | 0.65 | 0.91 | 1.01 | 0.92 | 0.65 | 0.71 | 1.41 | 0.49 | 0.80 | 0.60 | 1.14 | 0.44 | 0.33 | 0.01 | 0.28 | 0.70 |
| *Sortino* | 0.78 | 0.39 | 0.35 | 0.43 | 0.33 | 0.41 | 0.41 | 0.41 | 0.30 | 0.35 | 0.69 | 0.21 | 0.38 | 0.29 | 0.50 | 0.19 | 0.15 | 0.00 | 0.13 | 0.31 |
| *Kappa3* | 0.52 | 0.26 | 0.23 | 0.30 | 0.23 | 0.28 | 0.27 | 0.28 | 0.20 | 0.25 | 0.50 | 0.14 | 0.28 | 0.21 | 0.34 | 0.12 | 0.10 | 0.00 | 0.09 | 0.22 |
| *Sharpe* | 0.80 | 0.34 | 0.28 | 0.43 | 0.19 | 0.40 | 0.46 | 0.42 | 0.18 | 0.23 | 0.73 | 0.22 | 0.52 | 0.34 | 0.78 | 0.16 | 0.05 | -0.29 | 0.00 | 0.39 |
| *Std. dev* | 0.421 | 0.28 | 0.291 | 0.281 | 0.303 | 0.267 | 0.295 | 0.314 | 0.38 | 0.49 | 0.55 | 0.29 | 0.26 | 0.25 | 0.28 | 0.31 | 0.30 | 0.35 | 0.39 | 0.49 |
| *Annual R* | 0.465 | 0.203 | 0.186 | 0.229 | 0.159 | 0.213 | 0.244 | 0.24 | 0.174 | 0.222 | 0.47 | 0.11 | 0.19 | 0.14 | 0.27 | 0.10 | 0.06 | -0.06 | 0.05 | 0.24 |
| *Cum Ret* | 372 | 16 | 13 | 24 | 9 | 19 | 29 | 27 | 11 | 21 | 45 | 2 | 5 | 3 | 10 | 2 | 1 | 0 | 1 | 8 |
| *W DD* | -43% | -50% | -55% | -55% | -51% | -46% | -51% | -57% | -74% | -78% | -62% | -64% | -58% | -57% | -52% | -69% | -67% | -76% | -82% | -76% |
| *Skew* | 3.5 | -0.3 | 0.0 | 0.2 | 0.6 | -0.2 | -0.5 | -0.1 | 0.2 | 0.8 | 3.0 | -0.9 | 0.0 | -0.2 | -0.3 | -0.9 | -0.6 | -0.6 | -0.2 | -0.4 |
| *Ex Kurt* | 29.1 | 0.8 | 2.2 | 2.2 | 2.3 | 1.0 | 2.3 | 0.9 | 1.9 | 1.8 | 16.6 | 1.7 | 0.8 | 0.5 | 0.7 | 3.1 | 2.6 | 1.0 | 1.3 | 0.8 |
| | ***Panel C: 2000 - 2015*** | | | | | | | | | | ***Panel F: 2008 (Financial Crisis)*** | | | | | | | | | |
| *Up Pot* | 0.99 | 0.67 | 0.78 | 0.77 | 0.90 | 0.60 | 0.62 | 0.52 | 0.61 | 0.65 | 0.47 | 0.40 | 0.51 | 0.49 | 0.71 | 0.44 | 0.46 | 0.37 | 0.68 | 0.78 |
| *Inf Ratio* | 0.64 | 0.03 | -0.01 | -0.16 | 0.55 | -0.40 | -0.33 | -0.88 | -0.32 | -0.23 | -0.32 | -0.46 | -0.21 | -0.50 | 0.88 | -0.55 | -0.51 | -1.27 | 0.41 | 0.85 |
| *Omega* | 1.19 | 0.72 | 0.65 | 0.58 | 1.05 | 0.40 | 0.43 | 0.04 | 0.30 | 0.30 | -0.09 | -0.17 | -0.10 | -0.17 | 0.46 | -0.13 | -0.12 | -0.36 | 0.36 | 0.47 |
| *Sortino* | 0.54 | 0.28 | 0.31 | 0.28 | 0.46 | 0.17 | 0.19 | 0.02 | 0.14 | 0.15 | -0.04 | -0.08 | -0.05 | -0.10 | 0.22 | -0.06 | -0.06 | -0.21 | 0.18 | 0.25 |
| *Kappa3* | 0.38 | 0.18 | 0.22 | 0.20 | 0.31 | 0.11 | 0.12 | 0.01 | 0.10 | 0.11 | -0.03 | -0.06 | -0.04 | -0.08 | 0.17 | -0.05 | -0.05 | -0.17 | 0.14 | 0.19 |
| *Sharpe* | 0.72 | 0.43 | 0.43 | 0.35 | 0.74 | 0.15 | 0.17 | -0.22 | 0.04 | 0.03 | -0.40 | -0.50 | -0.40 | -0.52 | 0.23 | -0.47 | -0.45 | -0.78 | 0.10 | 0.25 |
| *Std. dev* | 0.377 | 0.248 | 0.238 | 0.23 | 0.251 | 0.275 | 0.277 | 0.31 | 0.359 | 0.47 | 0.41 | 0.38 | 0.35 | 0.36 | 0.41 | 0.51 | 0.47 | 0.48 | 0.49 | 0.49 |
| *Annual R* | 0.318 | 0.146 | 0.14 | 0.119 | 0.226 | 0.079 | 0.085 | -0.033 | 0.052 | 0.052 | -0.13 | -0.16 | -0.10 | -0.15 | 0.14 | -0.21 | -0.18 | -0.35 | 0.09 | 0.17 |
| *Cum Ret* | 71 | 7 | 7 | 5 | 22 | 2 | 3 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -1 | 0 | 0 |
| *W DD* | -62% | -64% | -58% | -57% | -52% | -69% | -67% | -76% | -82% | -76% | -62% | -64% | -56% | -56% | -52% | -67% | -65% | -72% | -54% | -57% |
| *Skew* | 1.5 | -1.1 | -0.2 | 0.0 | -0.2 | -0.9 | -0.6 | -0.5 | -0.1 | -0.2 | -0.6 | -1.2 | 0.1 | -0.2 | -0.4 | -0.7 | -0.4 | -0.5 | -0.5 | -0.4 |
| *Ex Kurt* | 7.7 | 2.9 | 0.8 | 1.0 | 1.0 | 3.7 | 2.9 | 1.4 | 1.7 | 0.5 | -0.2 | 0.6 | 0.0 | -0.9 | -0.3 | 0.4 | 0.3 | -0.7 | -0.3 | -0.8 |
| | ***Panel G: 1985 - 1989*** | | | | | | | | | | ***Panel J: 2000 - 2004*** | | | | | | | | | |
| *Up Pot* | 1.08 | 0.97 | 0.93 | 1.08 | 1.02 | 1.20 | 1.02 | 1.13 | 0.91 | 0.58 | 1.57 | 0.57 | 0.92 | 0.93 | 1.10 | 0.81 | 0.72 | 0.59 | 0.58 | 0.73 |
| *Inf Ratio* | 0.94 | 0.03 | 0.29 | 0.67 | -0.02 | 0.40 | 0.50 | 0.76 | -0.19 | -0.83 | 0.87 | -1.20 | -0.09 | -0.24 | 0.34 | -0.45 | -0.54 | -0.91 | -0.73 | 0.01 |
| *Omega* | 1.80 | 1.01 | 1.34 | 1.80 | 1.00 | 1.66 | 1.58 | 1.55 | 0.81 | 0.04 | 2.05 | 0.11 | 0.86 | 0.86 | 1.15 | 0.57 | 0.44 | 0.11 | 0.09 | 0.61 |
| *Sortino* | 0.69 | 0.49 | 0.53 | 0.69 | 0.51 | 0.75 | 0.63 | 0.69 | 0.41 | 0.02 | 1.05 | 0.06 | 0.43 | 0.43 | 0.59 | 0.29 | 0.22 | 0.06 | 0.05 | 0.28 |
| *Kappa3* | 0.45 | 0.35 | 0.34 | 0.45 | 0.36 | 0.54 | 0.41 | 0.48 | 0.30 | 0.02 | 0.79 | 0.04 | 0.31 | 0.31 | 0.43 | 0.22 | 0.15 | 0.04 | 0.03 | 0.20 |
| *Sharpe* | 0.90 | 0.38 | 0.47 | 0.66 | 0.28 | 0.66 | 0.72 | 0.76 | 0.19 | -0.43 | 0.87 | -0.19 | 0.49 | 0.51 | 0.75 | 0.27 | 0.15 | -0.19 | -0.23 | 0.24 |
| *Std. dev* | 0.315 | 0.298 | 0.333 | 0.314 | 0.359 | 0.269 | 0.237 | 0.319 | 0.323 | 0.417 | 0.66 | 0.27 | 0.25 | 0.20 | 0.26 | 0.26 | 0.28 | 0.36 | 0.44 | 0.58 |
| *Annual R* | 0.462 | 0.269 | 0.318 | 0.378 | 0.256 | 0.344 | 0.335 | 0.416 | 0.213 | -0.06 | 0.66 | 0.00 | 0.18 | 0.17 | 0.26 | 0.13 | 0.10 | -0.02 | -0.05 | 0.20 |
| *Cum Ret* | 6 | 2 | 3 | 4 | 2 | 3 | 3 | 5 | 2 | 0 | 12 | 0 | 1 | 1 | 2 | 1 | 1 | 0 | 0 | 2 |
| *W DD* | -42% | -37% | -43% | -36% | -38% | -39% | -38% | -37% | -36% | -59% | -55% | -57% | -35% | -33% | -29% | -53% | -53% | -75% | -82% | -76% |
| *Skew* | -0.6 | -0.1 | 0.2 | 0.7 | 1.2 | 0.6 | -1.1 | -0.1 | 0.4 | 0.6 | 3.2 | -0.1 | 0.4 | 0.0 | 0.3 | 0.3 | -0.2 | -0.4 | 0.0 | -0.4 |
| *Ex Kurt* | 1.7 | -0.3 | 2.4 | 3.1 | 2.6 | 1.2 | 1.9 | 0.3 | 0.4 | 1.7 | 14.0 | 1.1 | 1.0 | 0.3 | -0.3 | 0.3 | 1.2 | 0.4 | 0.9 | 0.3 |
| | ***Panel H: 1990 - 1994*** | | | | | | | | | | ***Panel K: 2005 - 2009*** | | | | | | | | | |
| *Up Pot* | 1.07 | 0.74 | 0.59 | 0.61 | 0.75 | 0.74 | 0.80 | 0.67 | 0.68 | 0.90 | 0.88 | 0.71 | 0.83 | 0.71 | 0.85 | 0.55 | 0.53 | 0.42 | 0.67 | 0.86 |
| *Inf Ratio* | 0.61 | -0.42 | -0.63 | -0.67 | -0.14 | 0.05 | 0.63 | -0.38 | -0.15 | 0.20 | 0.44 | 0.34 | 0.10 | -0.43 | 0.64 | -0.53 | -0.88 | -1.38 | -0.10 | 0.38 |
| *Omega* | 1.03 | 0.32 | 0.24 | 0.21 | 0.45 | 0.58 | 0.90 | 0.32 | 0.41 | 0.65 | 0.87 | 0.93 | 0.75 | 0.44 | 1.13 | 0.35 | 0.23 | -0.11 | 0.59 | 0.83 |
| *Sortino* | 0.54 | 0.18 | 0.11 | 0.11 | 0.23 | 0.27 | 0.38 | 0.16 | 0.20 | 0.35 | 0.41 | 0.34 | 0.36 | 0.22 | 0.45 | 0.14 | 0.10 | -0.05 | 0.25 | 0.39 |
| *Kappa3* | 0.41 | 0.13 | 0.08 | 0.08 | 0.17 | 0.20 | 0.26 | 0.12 | 0.14 | 0.27 | 0.30 | 0.23 | 0.26 | 0.16 | 0.31 | 0.10 | 0.07 | -0.04 | 0.17 | 0.29 |
| *Sharpe* | 0.50 | -0.10 | -0.20 | -0.21 | 0.05 | 0.16 | 0.42 | -0.09 | -0.03 | 0.21 | 0.62 | 0.63 | 0.54 | 0.22 | 0.80 | 0.08 | -0.04 | -0.40 | 0.32 | 0.63 |
| *Std. dev* | 0.328 | 0.27 | 0.284 | 0.303 | 0.311 | 0.283 | 0.354 | 0.352 | 0.489 | 0.589 | 0.40 | 0.30 | 0.28 | 0.29 | 0.30 | 0.36 | 0.32 | 0.34 | 0.34 | 0.38 |
| *Annual R* | 0.28 | 0.072 | 0.038 | 0.031 | 0.119 | 0.15 | 0.263 | 0.067 | 0.089 | 0.238 | 0.29 | 0.23 | 0.20 | 0.11 | 0.28 | 0.07 | 0.03 | -0.10 | 0.15 | 0.28 |
| *Cum Ret* | 2 | 0 | 0 | 0 | 1 | 1 | 2 | 0 | 1 | 2 | 3 | 2 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 2 |
| *W DD* | -43% | -50% | -55% | -55% | -51% | -46% | -51% | -57% | -74% | -74% | -62% | -64% | -58% | -57% | -52% | -69% | -67% | -75% | -54% | -57% |
| *Skew* | 0.7 | 0.0 | -0.7 | -0.2 | -0.2 | -0.7 | -0.5 | 0.0 | 0.2 | 0.7 | -0.1 | -1.6 | -0.2 | -0.2 | -0.6 | -1.2 | -0.8 | -0.9 | -0.5 | -0.4 |
| *Ex Kurt* | 0.6 | -0.1 | 1.1 | 0.0 | 0.2 | -0.1 | 1.4 | 0.3 | 1.1 | 0.4 | 0.6 | 2.8 | 0.6 | 0.0 | 1.2 | 3.1 | 3.2 | 1.7 | 1.7 | 0.1 |
| | ***Panel I: 1995 - 1999*** | | | | | | | | | | ***Panel L: 2010 - 2014*** | | | | | | | | | |
| *Up Pot* | 1.15 | 0.89 | 0.86 | 1.08 | 0.78 | 0.76 | 0.75 | 0.89 | 0.85 | 1.00 | 0.89 | 0.78 | 0.67 | 0.77 | 0.77 | 0.65 | 0.78 | 0.65 | 0.57 | 0.56 |
| *Inf Ratio* | 1.23 | 0.55 | -0.20 | 0.69 | -0.82 | -0.50 | -0.22 | 0.22 | 0.07 | 0.68 | 0.45 | 0.64 | -0.20 | -0.25 | 0.03 | -0.10 | 0.41 | -0.40 | -0.33 | -0.50 |
| *Omega* | 2.31 | 1.72 | 1.00 | 1.96 | 0.51 | 0.70 | 0.87 | 1.26 | 0.96 | 1.58 | 1.05 | 1.19 | 0.38 | 0.38 | 0.57 | 0.45 | 0.97 | 0.24 | 0.22 | 0.02 |
| *Sortino* | 0.80 | 0.56 | 0.43 | 0.72 | 0.26 | 0.31 | 0.35 | 0.49 | 0.41 | 0.61 | 0.45 | 0.42 | 0.19 | 0.21 | 0.28 | 0.20 | 0.39 | 0.12 | 0.10 | 0.01 |
| *Kappa3* | 0.50 | 0.32 | 0.30 | 0.46 | 0.18 | 0.21 | 0.22 | 0.30 | 0.27 | 0.40 | 0.31 | 0.27 | 0.13 | 0.16 | 0.20 | 0.14 | 0.24 | 0.09 | 0.07 | 0.01 |
| *Sharpe* | 1.27 | 0.95 | 0.58 | 1.11 | 0.20 | 0.37 | 0.42 | 0.73 | 0.55 | 0.82 | 0.61 | 0.83 | 0.23 | 0.23 | 0.40 | 0.31 | 0.65 | 0.07 | 0.03 | -0.23 |
| *Std. dev* | 0.32 | 0.26 | 0.22 | 0.22 | 0.24 | 0.26 | 0.29 | 0.26 | 0.32 | 0.44 | 0.29 | 0.20 | 0.22 | 0.20 | 0.20 | 0.20 | 0.22 | 0.24 | 0.28 | 0.46 |
| *Annual R* | 0.47 | 0.31 | 0.19 | 0.31 | 0.11 | 0.16 | 0.18 | 0.25 | 0.24 | 0.43 | 0.20 | 0.19 | 0.07 | 0.07 | 0.10 | 0.08 | 0.17 | 0.04 | 0.03 | -0.09 |
| *Cum Ret* | 6 | 3 | 1 | 3 | 1 | 1 | 1 | 2 | 2 | 5 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| *W DD* | -38% | -44% | -28% | -22% | -31% | -36% | -45% | -38% | -35% | -59% | -30% | -26% | -33% | -26% | -24% | -40% | -30% | -39% | -45% | -74% |
| *Skew* | 0.1 | -1.1 | -0.1 | -0.1 | 0.1 | -0.5 | -0.1 | -0.5 | 0.0 | 1.0 | 2.2 | -1.0 | -0.3 | 0.9 | 0.0 | -0.9 | -0.3 | 0.2 | -0.2 | 0.1 |
| *Ex Kurt* | 1.9 | 5.0 | 1.4 | 2.7 | 0.9 | 1.5 | 3.1 | 3.8 | 1.7 | 4.5 | 11.8 | 2.7 | 0.5 | 2.4 | 0.6 | 0.7 | 2.3 | 0.6 | 1.5 | 0.2 |

### *Table 4: : Performance Measures Cross-Sectional Sector Momentum*

This table shows the performance measures and descriptive statistics for all XSS-MOM decile portfolios P1 to P10 using a j = 12 month-look back period. Panel B-E show a set of longer sub-sample periods in addition to 2008 the financial crisis in Panel F. Panel G-L show a set of five-year sub-sample periods

| J=12 | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Panel A: 1985 - 2015*** | | | | | | | | | | ***Panel D: 1990 - 1999*** | | | | | | | | | |
| *Up Pot* | 0.95 | 0.94 | 0.88 | 0.76 | 0.66 | 0.67 | 0.63 | 0.60 | 0.63 | 0.66 | 0.95 | 0.88 | 0.74 | 0.76 | 0.80 | 0.73 | 0.65 | 0.63 | 0.76 | 0.76 |
| *Inf Ratio* | 0.55 | 0.33 | 0.22 | -0.17 | -0.68 | -0.69 | -0.83 | -0.80 | -0.64 | -0.50 | 0.48 | 0.30 | 0.02 | -0.20 | -0.37 | -0.60 | -0.82 | -0.81 | -0.61 | -0.31 |
| *Omega* | 1.17 | 1.14 | 1.14 | 0.88 | 0.58 | 0.51 | 0.33 | 0.19 | 0.23 | 0.25 | 1.14 | 1.15 | 1.05 | 0.90 | 0.78 | 0.58 | 0.36 | 0.22 | 0.34 | 0.44 |
| *Sortino* | 0.51 | 0.50 | 0.47 | 0.35 | 0.24 | 0.23 | 0.16 | 0.10 | 0.12 | 0.13 | 0.51 | 0.47 | 0.38 | 0.36 | 0.35 | 0.27 | 0.17 | 0.11 | 0.19 | 0.23 |
| *Kappa3* | 0.35 | 0.34 | 0.30 | 0.23 | 0.16 | 0.16 | 0.11 | 0.07 | 0.08 | 0.09 | 0.35 | 0.31 | 0.23 | 0.22 | 0.24 | 0.19 | 0.12 | 0.08 | 0.15 | 0.17 |
| *Sharpe* | 0.71 | 0.63 | 0.59 | 0.38 | 0.16 | 0.12 | -0.03 | -0.15 | -0.10 | -0.07 | 0.64 | 0.54 | 0.43 | 0.33 | 0.29 | 0.14 | -0.05 | -0.17 | -0.02 | 0.10 |
| *Std. dev* | 0.29 | 0.25 | 0.23 | 0.23 | 0.23 | 0.23 | 0.23 | 0.26 | 0.30 | 0.35 | 0.28 | 0.27 | 0.23 | 0.24 | 0.23 | 0.22 | 0.23 | 0.24 | 0.26 | 0.33 |
| *Annual R* | 0.28 | 0.24 | 0.21 | 0.16 | 0.10 | 0.09 | 0.06 | 0.03 | 0.04 | 0.04 | 0.27 | 0.23 | 0.19 | 0.16 | 0.15 | 0.11 | 0.07 | 0.03 | 0.07 | 0.11 |
| *Cum Ret* | 2230 | 686 | 385 | 100 | 21 | 15 | 5 | 1 | 2 | 3 | 10 | 7 | 4 | 4 | 3 | 2 | 1 | 0 | 1 | 2 |
| *W DD* | -63% | -46% | -43% | -50% | -59% | -62% | -58% | -63% | -74% | -76% | -48% | -42% | -38% | -39% | -34% | -40% | -50% | -55% | -46% | -54% |
| *Skew* | 0.01 | 0.16 | -0.14 | -0.23 | -0.49 | -0.09 | -0.20 | -0.05 | -0.25 | -0.05 | 0.05 | 0.38 | -0.99 | -0.37 | 0.05 | -0.04 | -0.17 | 0.15 | 0.54 | 0.20 |
| *Ex Kurt* | 4.51 | 4.96 | 5.37 | 6.16 | 5.55 | 4.74 | 4.37 | 4.04 | 6.12 | 4.85 | 4.48 | 6.81 | 6.79 | 6.01 | 4.41 | 4.29 | 4.24 | 3.70 | 4.25 | 4.43 |
| | ***Panel B: 1985 - 2000*** | | | | | | | | | | ***Panel E: 2000 - 2009*** | | | | | | | | | |
| *Up Pot* | 1.01 | 0.98 | 0.82 | 0.76 | 0.67 | 0.67 | 0.63 | 0.61 | 0.62 | 0.64 | 0.90 | 0.96 | 0.96 | 0.82 | 0.70 | 0.74 | 0.64 | 0.55 | 0.66 | 0.73 |
| *Inf Ratio* | 0.58 | 0.35 | -0.04 | -0.55 | -1.12 | -1.17 | -1.08 | -0.86 | -0.67 | -0.57 | 0.43 | 0.28 | 0.20 | 0.13 | -0.32 | -0.36 | -0.81 | -1.21 | -0.91 | -0.45 |
| *Omega* | 1.36 | 1.36 | 1.16 | 0.84 | 0.53 | 0.44 | 0.32 | 0.19 | 0.25 | 0.27 | 1.00 | 1.06 | 1.08 | 1.02 | 0.74 | 0.65 | 0.36 | 0.10 | 0.20 | 0.32 |
| *Sortino* | 0.58 | 0.56 | 0.44 | 0.35 | 0.23 | 0.21 | 0.15 | 0.10 | 0.12 | 0.14 | 0.45 | 0.50 | 0.50 | 0.41 | 0.30 | 0.29 | 0.17 | 0.05 | 0.11 | 0.18 |
| *Kappa3* | 0.40 | 0.38 | 0.27 | 0.22 | 0.15 | 0.14 | 0.11 | 0.07 | 0.08 | 0.09 | 0.32 | 0.35 | 0.35 | 0.27 | 0.19 | 0.20 | 0.12 | 0.04 | 0.08 | 0.13 |
| *Sharpe* | 0.72 | 0.63 | 0.44 | 0.23 | 0.01 | -0.07 | -0.17 | -0.24 | -0.17 | -0.13 | 0.68 | 0.71 | 0.70 | 0.63 | 0.39 | 0.34 | 0.08 | -0.18 | -0.05 | 0.08 |
| *Std. dev* | 0.30 | 0.27 | 0.25 | 0.25 | 0.24 | 0.22 | 0.23 | 0.28 | 0.33 | 0.37 | 0.31 | 0.26 | 0.24 | 0.24 | 0.25 | 0.26 | 0.25 | 0.25 | 0.29 | 0.35 |
| *Annual R* | 0.33 | 0.28 | 0.21 | 0.16 | 0.10 | 0.08 | 0.06 | 0.02 | 0.04 | 0.05 | 0.27 | 0.23 | 0.22 | 0.21 | 0.15 | 0.14 | 0.07 | 0.00 | 0.03 | 0.08 |
| *Cum Ret* | 84 | 46 | 19 | 9 | 3 | 2 | 1 | 0 | 1 | 1 | 10 | 7 | 6 | 5 | 3 | 3 | 1 | 0 | 0 | 1 |
| *W DD* | -48% | -42% | -38% | -39% | -51% | -43% | -55% | -63% | -74% | -76% | -63% | -46% | -43% | -50% | -59% | -62% | -58% | -62% | -63% | -69% |
| *Skew* | 0.15 | 0.26 | -0.39 | -0.01 | -0.39 | -0.23 | -0.28 | 0.10 | -0.36 | -0.31 | -0.06 | 0.03 | 0.02 | -0.59 | -0.67 | -0.05 | -0.11 | -0.37 | -0.01 | 0.30 |
| *Ex Kurt* | 4.67 | 5.64 | 6.08 | 6.20 | 5.20 | 4.49 | 4.45 | 3.93 | 7.01 | 5.58 | 4.39 | 3.58 | 3.49 | 5.02 | 5.33 | 4.25 | 4.26 | 4.17 | 3.07 | 3.51 |
| | ***Panel C: 2000 - 2015*** | | | | | | | | | | ***Panel F: 2008 (Financial Crisis)*** | | | | | | | | | |
| *Up Pot* | 0.89 | 0.89 | 0.96 | 0.75 | 0.64 | 0.68 | 0.63 | 0.60 | 0.66 | 0.69 | 0.42 | 0.65 | 0.69 | 0.52 | 0.50 | 0.58 | 0.49 | 0.43 | 0.66 | 0.99 |
| *Inf Ratio* | 0.53 | 0.30 | 0.47 | 0.16 | -0.29 | -0.27 | -0.58 | -0.76 | -0.64 | -0.42 | -1.06 | 0.80 | 0.83 | 0.37 | 0.02 | 0.20 | -0.08 | -0.49 | 0.62 | 1.38 |
| *Omega* | 0.98 | 0.92 | 1.13 | 0.92 | 0.64 | 0.59 | 0.34 | 0.20 | 0.21 | 0.22 | -0.25 | 0.30 | 0.38 | 0.18 | 0.05 | 0.11 | -0.01 | -0.19 | 0.29 | 0.94 |
| *Sortino* | 0.44 | 0.43 | 0.51 | 0.36 | 0.25 | 0.25 | 0.16 | 0.10 | 0.11 | 0.12 | -0.14 | 0.15 | 0.19 | 0.08 | 0.02 | 0.06 | -0.01 | -0.10 | 0.15 | 0.48 |
| *Kappa3* | 0.31 | 0.30 | 0.36 | 0.23 | 0.16 | 0.17 | 0.11 | 0.07 | 0.08 | 0.09 | -0.11 | 0.11 | 0.14 | 0.06 | 0.02 | 0.04 | -0.01 | -0.08 | 0.11 | 0.35 |
| *Sharpe* | 0.71 | 0.63 | 0.76 | 0.57 | 0.32 | 0.29 | 0.11 | -0.03 | 0.00 | 0.01 | -0.63 | 0.08 | 0.16 | -0.10 | -0.24 | -0.16 | -0.30 | -0.52 | 0.05 | 0.64 |
| *Std. dev* | 0.27 | 0.24 | 0.22 | 0.22 | 0.22 | 0.23 | 0.24 | 0.24 | 0.27 | 0.33 | 0.39 | 0.31 | 0.32 | 0.35 | 0.38 | 0.38 | 0.37 | 0.36 | 0.39 | 0.48 |
| *Annual R* | 0.24 | 0.19 | 0.21 | 0.16 | 0.11 | 0.11 | 0.06 | 0.03 | 0.04 | 0.04 | -0.21 | 0.07 | 0.10 | 0.01 | -0.05 | -0.02 | -0.07 | -0.15 | 0.06 | 0.36 |
| *Cum Ret* | 25 | 14 | 18 | 9 | 4 | 4 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| *W DD* | -63% | -46% | -43% | -50% | -59% | -62% | -58% | -62% | -63% | -69% | -63% | -39% | -43% | -49% | -57% | -56% | -52% | -56% | -52% | -53% |
| *Skew* | -0.21 | -0.05 | 0.20 | -0.56 | -0.62 | 0.02 | -0.12 | -0.29 | -0.04 | 0.29 | -0.57 | -0.64 | -0.37 | -0.70 | -0.50 | -0.08 | -0.13 | -0.42 | -0.40 | 0.25 |
| *Ex Kurt* | 4.12 | 3.46 | 4.21 | 5.66 | 5.96 | 4.89 | 4.28 | 3.99 | 3.11 | 3.60 | 2.01 | 2.73 | 2.56 | 3.95 | 3.50 | 2.87 | 3.36 | 3.18 | 2.88 | 2.93 |
| | ***Panel G: 1985 - 1989*** | | | | | | | | | | ***Panel J: 2000 - 2004*** | | | | | | | | | |
| *Up Pot* | 0.93 | 1.06 | 0.95 | 0.75 | 0.50 | 0.54 | 0.57 | 0.62 | 0.56 | 0.54 | 1.13 | 0.92 | 0.91 | 0.92 | 0.77 | 0.79 | 0.72 | 0.61 | 0.64 | 0.59 |
| *Inf Ratio* | 0.30 | 0.32 | -0.03 | -0.94 | -2.33 | -2.24 | -1.48 | -0.87 | -0.68 | -0.75 | 0.60 | -0.27 | -0.34 | -0.08 | -0.45 | -0.53 | -0.89 | -1.21 | -1.26 | -1.03 |
| *Omega* | 1.26 | 1.49 | 1.26 | 0.69 | 0.15 | 0.17 | 0.17 | 0.15 | 0.19 | 0.11 | 1.18 | 0.72 | 0.78 | 1.02 | 0.76 | 0.61 | 0.33 | 0.13 | 0.03 | 0.00 |
| *Sortino* | 0.52 | 0.64 | 0.53 | 0.31 | 0.06 | 0.08 | 0.08 | 0.08 | 0.09 | 0.06 | 0.61 | 0.38 | 0.40 | 0.46 | 0.33 | 0.30 | 0.18 | 0.07 | 0.02 | 0.00 |
| *Kappa3* | 0.36 | 0.44 | 0.36 | 0.21 | 0.04 | 0.05 | 0.06 | 0.06 | 0.06 | 0.04 | 0.45 | 0.29 | 0.30 | 0.32 | 0.23 | 0.22 | 0.14 | 0.05 | 0.01 | 0.00 |
| *Sharpe* | 0.53 | 0.61 | 0.37 | 0.00 | -0.47 | -0.51 | -0.47 | -0.34 | -0.31 | -0.38 | 0.79 | 0.35 | 0.37 | 0.56 | 0.35 | 0.26 | 0.03 | -0.19 | -0.28 | -0.31 |
| *Std. dev* | 0.29 | 0.25 | 0.27 | 0.28 | 0.25 | 0.21 | 0.23 | 0.35 | 0.45 | 0.46 | 0.32 | 0.26 | 0.23 | 0.23 | 0.22 | 0.24 | 0.24 | 0.22 | 0.28 | 0.34 |
| *Annual R* | 0.31 | 0.32 | 0.26 | 0.14 | 0.01 | 0.02 | 0.02 | 0.01 | -0.02 | -0.05 | 0.33 | 0.15 | 0.14 | 0.19 | 0.14 | 0.12 | 0.06 | 0.01 | -0.03 | -0.06 |
| *Cum Ret* | 3 | 3 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| *W DD* | -34% | -32% | -32% | -38% | -51% | -43% | -48% | -59% | -74% | -76% | -47% | -46% | -40% | -35% | -38% | -35% | -51% | -58% | -63% | -69% |
| *Skew* | -0.67 | -0.27 | 0.33 | 0.44 | -1.01 | -0.80 | -0.46 | 0.05 | -0.69 | -0.60 | 0.66 | 0.84 | 0.74 | 0.11 | -0.14 | 0.38 | 0.33 | 0.07 | 0.29 | 0.07 |
| *Ex Kurt* | 3.58 | 3.11 | 5.01 | 6.18 | 5.84 | 4.98 | 4.70 | 3.22 | 5.70 | 5.14 | 4.39 | 4.07 | 3.96 | 3.30 | 3.52 | 3.85 | 2.98 | 2.95 | 2.39 | 2.67 |
| | ***Panel H: 1990 - 1994*** | | | | | | | | | | ***Panel K: 2005 - 2009*** | | | | | | | | | |
| *Up Pot* | 0.87 | 0.76 | 0.69 | 0.73 | 0.79 | 0.73 | 0.61 | 0.53 | 0.69 | 0.79 | 0.73 | 1.00 | 1.01 | 0.76 | 0.67 | 0.72 | 0.59 | 0.51 | 0.68 | 0.92 |
| *Inf Ratio* | 0.35 | 0.02 | -0.08 | -0.07 | -0.06 | -0.44 | -0.92 | -0.88 | -0.62 | -0.27 | 0.23 | 1.15 | 0.84 | 0.34 | -0.17 | -0.19 | -0.73 | -1.20 | -0.49 | 0.20 |
| *Omega* | 0.79 | 0.64 | 0.64 | 0.63 | 0.60 | 0.40 | 0.06 | -0.05 | 0.14 | 0.33 | 0.82 | 1.44 | 1.36 | 1.02 | 0.72 | 0.69 | 0.38 | 0.08 | 0.43 | 0.78 |
| *Sortino* | 0.39 | 0.30 | 0.27 | 0.28 | 0.29 | 0.21 | 0.03 | -0.03 | 0.09 | 0.19 | 0.33 | 0.59 | 0.58 | 0.39 | 0.28 | 0.29 | 0.16 | 0.04 | 0.20 | 0.40 |
| *Kappa3* | 0.28 | 0.20 | 0.18 | 0.19 | 0.21 | 0.16 | 0.03 | -0.02 | 0.07 | 0.15 | 0.23 | 0.41 | 0.40 | 0.25 | 0.18 | 0.20 | 0.11 | 0.03 | 0.14 | 0.29 |
| *Sharpe* | 0.32 | 0.15 | 0.11 | 0.12 | 0.13 | -0.04 | -0.40 | -0.53 | -0.29 | -0.07 | 0.56 | 1.11 | 1.04 | 0.68 | 0.42 | 0.40 | 0.13 | -0.17 | 0.19 | 0.51 |
| *Std. dev* | 0.29 | 0.27 | 0.25 | 0.26 | 0.25 | 0.25 | 0.26 | 0.27 | 0.27 | 0.32 | 0.30 | 0.25 | 0.25 | 0.26 | 0.27 | 0.27 | 0.27 | 0.27 | 0.30 | 0.36 |
| *Annual R* | 0.20 | 0.15 | 0.13 | 0.14 | 0.14 | 0.09 | -0.01 | -0.06 | 0.02 | 0.08 | 0.21 | 0.33 | 0.30 | 0.22 | 0.16 | 0.15 | 0.07 | -0.01 | 0.10 | 0.23 |
| *Cum Ret* | 2 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 2 | 3 | 3 | 2 | 1 | 1 | 0 | 0 | 1 | 2 |
| *W DD* | -48% | -37% | -38% | -39% | -34% | -38% | -50% | -55% | -39% | -38% | -63% | -39% | -43% | -50% | -59% | -62% | -58% | -62% | -57% | -55% |
| *Skew* | -0.11 | -0.30 | -0.70 | -0.51 | -0.27 | -0.27 | 0.02 | -0.03 | 0.24 | 0.50 | -1.01 | -0.83 | -0.58 | -1.05 | -0.95 | -0.37 | -0.43 | -0.60 | -0.28 | 0.49 |
| *Ex Kurt* | 2.91 | 3.82 | 4.45 | 4.27 | 3.35 | 2.56 | 2.53 | 2.71 | 2.22 | 2.61 | 3.99 | 3.63 | 3.49 | 5.95 | 5.84 | 4.47 | 5.00 | 4.46 | 3.73 | 4.05 |
| | ***Panel I: 1995 - 1999*** | | | | | | | | | | ***Panel L: 2010 - 2014*** | | | | | | | | | |
| *Up Pot* | 1.04 | 1.05 | 0.81 | 0.80 | 0.86 | 0.75 | 0.72 | 0.88 | 0.85 | 0.74 | 1.25 | 0.94 | 1.11 | 0.71 | 0.56 | 0.58 | 0.55 | 0.59 | 0.56 | 0.49 |
| *Inf Ratio* | 0.61 | 0.56 | 0.15 | -0.33 | -0.61 | -0.76 | -0.67 | -0.70 | -0.58 | -0.34 | 1.13 | 0.69 | 1.13 | 0.14 | -0.36 | -0.29 | -0.66 | -0.59 | -0.87 | -0.93 |
| *Omega* | 1.62 | 2.00 | 1.73 | 1.37 | 1.10 | 0.91 | 0.98 | 0.75 | 0.60 | 0.56 | 1.63 | 1.08 | 1.47 | 0.80 | 0.48 | 0.48 | 0.17 | 0.14 | -0.04 | -0.18 |
| *Sortino* | 0.64 | 0.70 | 0.51 | 0.46 | 0.45 | 0.36 | 0.35 | 0.38 | 0.32 | 0.27 | 0.78 | 0.49 | 0.66 | 0.31 | 0.18 | 0.19 | 0.08 | 0.07 | -0.02 | -0.11 |
| *Kappa3* | 0.42 | 0.43 | 0.28 | 0.26 | 0.29 | 0.23 | 0.22 | 0.26 | 0.23 | 0.18 | 0.56 | 0.34 | 0.46 | 0.21 | 0.12 | 0.13 | 0.06 | 0.05 | -0.02 | -0.08 |
| *Sharpe* | 1.00 | 0.96 | 0.82 | 0.58 | 0.48 | 0.38 | 0.43 | 0.34 | 0.29 | 0.27 | 1.15 | 0.80 | 1.02 | 0.54 | 0.24 | 0.22 | -0.01 | -0.03 | -0.25 | -0.47 |
| *Std. dev* | 0.28 | 0.27 | 0.22 | 0.22 | 0.21 | 0.20 | 0.21 | 0.21 | 0.26 | 0.33 | 0.27 | 0.23 | 0.21 | 0.16 | 0.17 | 0.20 | 0.20 | 0.22 | 0.23 | 0.29 |
| *Annual R* | 0.35 | 0.33 | 0.24 | 0.19 | 0.16 | 0.13 | 0.15 | 0.13 | 0.13 | 0.15 | 0.33 | 0.21 | 0.24 | 0.11 | 0.06 | 0.07 | 0.02 | 0.01 | -0.04 | -0.12 |
| *Cum Ret* | 3 | 3 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 2 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| *W DD* | -32% | -42% | -36% | -31% | -30% | -40% | -42% | -36% | -46% | -54% | -22% | -26% | -25% | -27% | -28% | -28% | -32% | -32% | -49% | -64% |
| *Skew* | 0.24 | 1.04 | -1.34 | -0.12 | 0.62 | 0.40 | -0.39 | 0.72 | 0.88 | -0.07 | 0.88 | 0.15 | 0.69 | -0.63 | -0.56 | 0.15 | -0.35 | -0.43 | -0.06 | -0.05 |
| *Ex Kurt* | 6.20 | 9.29 | 10.45 | 8.62 | 6.21 | 7.55 | 7.77 | 5.27 | 6.41 | 6.01 | 5.15 | 3.69 | 5.67 | 4.89 | 5.32 | 5.87 | 3.95 | 2.98 | 2.59 | 3.10 |

## 5.2 Time-Series Momentum

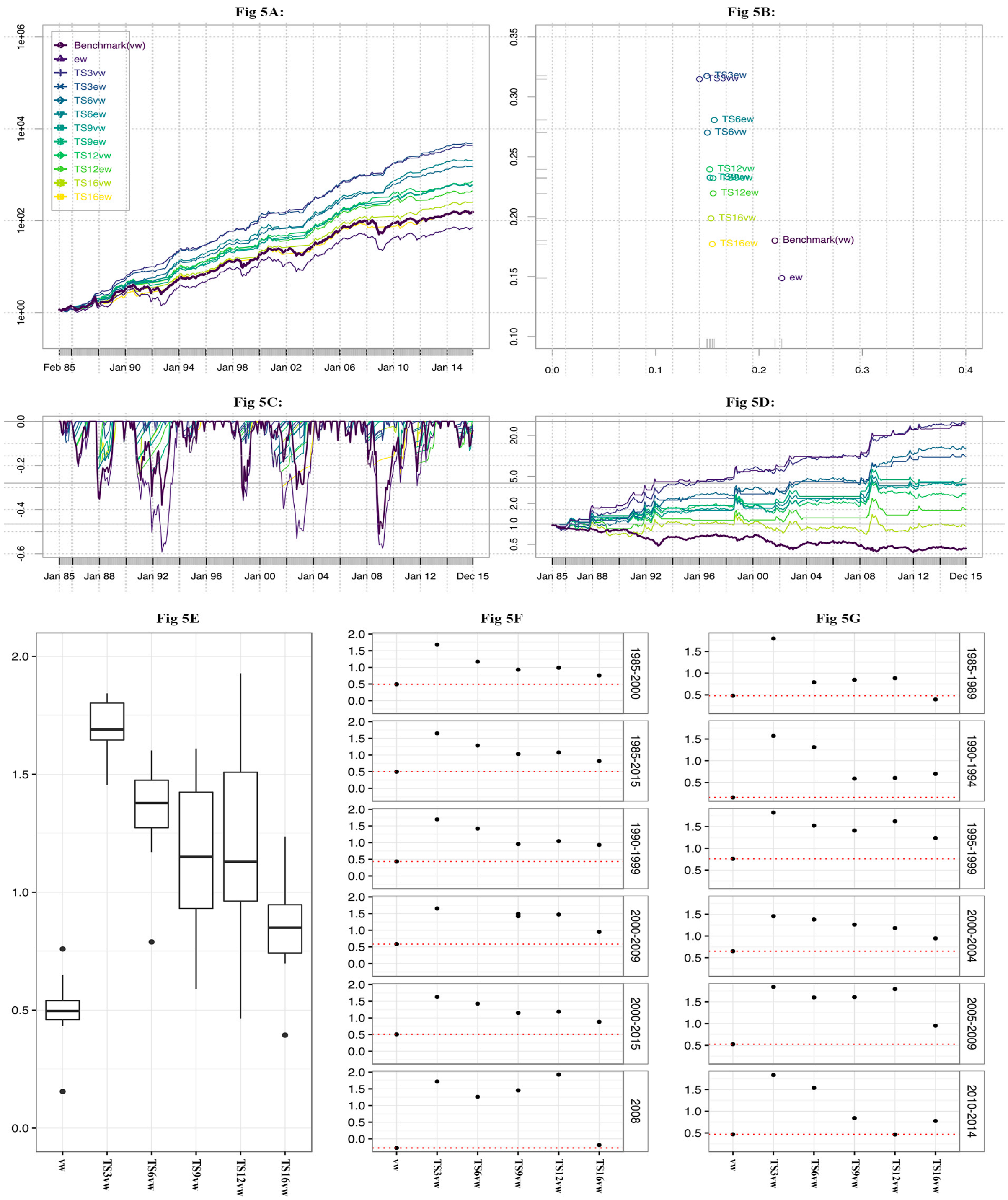
Section 5.2.1 and 5.2.2 presentation the results of time-series momentum compared to buy & hold on the constructed market and sector portfolios. Section 5.2.3 presents the results from the combination of time-series and the cross-sectional momentum portfolios (Dual Momentum) presented in chapter 5.2.4. Given the robust performance of all the cross-sectional look-back periods j, and that most prior academic studies often use a twelve-month look-back period, I will present the coming analysis by using a fixed j = 12-month cross-sectional look back period. Thus in the continuing section(s), only changes in the time-series look-back parameter, j* will be analyzed.

### 5.2.1 Market Portfolios

Figure 5a, b and d show that the addition of the time-series strategy to a broad and diversified market portfolio persistently deliver over-performance relative to a passive buy and hold "vw" and "ew" positions. Another prevalent observation is the superior performance of using a look-back period of j*= 3 months in the time-series filter and the marginal decrease in performance with increasing look-back periods j*>3. The source of value-added from the time-series overlay is the avoidance of downtrending markets and looking at Fig 5c, this attempt seems most successfully achieved using shorter look back periods. The look-back periods j*=3, 6, 9 and 12 appear highly robust and are able to sidestep a major portion of the financial crisis. However j*=16 performs very similar to its buy and hold counterparts. From Figure 5e, f, and g, all market portfolios with the application of the time-series momentum overlay substantially outperform the buy & hold market portfolios across all twelve-sample periods. As noted, the performance of j* = 3 show the greatest persistence across all twelve periods. Look-back periods of >j*=3 months in general appears to give a marginally diminishing performance. From the Performance measures in table 5 we note a positive Skewness in the time-series portfolios compared to the B&H distribution of returns. Overall, we note a striking decrease in drawdowns with the application of time-series overlay, e.g., from 1985 to 2015 the application of a j*=3 month time-series filter yielded a 32% return with the worst drawdown of only 10%, compared to an annualized return of 18% and worst drawdown of 51% for the buy and hold vw (benchmark) portfolio The results from table 5 underline the applicability of applying time-series momentum either to an equal or value-weighted broad market portfolio.

***Figure 5: Time-Series compared to Buy & Hold Market Portfolios Illustrations***

Figure 5a show the cumulative log returns for the buy and hold value and equally -weighted benchmark (vw and ew) portfolio and the vw/vw portfolio with applied time-series momentum(TSj*vw, TSj*ew) using j* = 3, 6, 9, 12 and 16 month look-back periods. It is assumed that NOK 1 was invested January 1985 to December 2015. Fig 5b illustrates the additional risk for we gain relative to returns. Fig 5c show the drawdown profiles. The dashed lines represent portfolios with time-series overlay. Fig 5d presents the performance relative to benchmark (vw). The box plot in Fig 5e shows the Sharpe-ratio for the B&H vs. Time-Series portfolios. Each box contains statistical information for the Sharpe ratio over the entire sample period as well as all sub-sample periods, i.e., a total of n =12 observations. Outliers are represented with dots outside the box. Fig 5f show the Sharpe-ratio pattern for the for all n = 12 sub-sample periods.



### *Table 5: Time-Series compared to Buy & Hold Market Portfolios Performance measures*

This table shows the performance measures and descriptive statistics during a set of different sample periods for both the value and equally weighted market (benchmark) portfolios with and without j* = 3, 6, 9, 12, 16 look-back periods (TS3, TS6, TS9, TS12, TS16, respectively).

| | BH | | TS3 | | TS6 | | TS9 | | TS12 | | TS16 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | vw | ew | vw | ew | vw | ew | vw | ew | vw | ew | vw | ew |
| *Panel A: 1985 - 2015* | | | | | | | | | | | | |
| *Up* | 0.83 | 0.77 | 2.03 | 1.95 | 1.43 | 1.50 | 1.22 | 1.19 | 1.25 | 1.15 | 1.06 | 0.98 |
| *IR* | - | -0.32 | 0.89 | 0.80 | 0.61 | 0.60 | 0.35 | 0.31 | 0.40 | 0.24 | 0.12 | -0.02 |
| *Omega* | 0.95 | 0.75 | 5.20 | 5.10 | 3.47 | 3.50 | 2.49 | 2.39 | 2.67 | 2.26 | 2.05 | 1.67 |
| *Sortino* | 0.41 | 0.33 | 1.71 | 1.63 | 1.11 | 1.17 | 0.87 | 0.84 | 0.91 | 0.79 | 0.71 | 0.62 |
| *Kappa3* | 0.27 | 0.22 | 1.08 | 1.04 | 0.61 | 0.70 | 0.51 | 0.53 | 0.52 | 0.50 | 0.42 | 0.40 |
| *Sharpe* | 0.50 | 0.35 | 1.65 | 1.59 | 1.29 | 1.29 | 1.03 | 1.01 | 1.08 | 0.93 | 0.82 | 0.68 |
| *Std. dev* | 0.22 | 0.22 | 0.14 | 0.15 | 0.15 | 0.16 | 0.15 | 0.16 | 0.15 | 0.16 | 0.15 | 0.16 |
| *Annual R* | 0.18 | 0.15 | 0.32 | 0.32 | 0.27 | 0.28 | 0.23 | 0.23 | 0.24 | 0.22 | 0.20 | 0.18 |
| *Cum Ret* | 168.4 | 72.8 | 4841.6 | 5155.8 | 1659.8 | 2139.5 | 652.7 | 644.5 | 776.6 | 468.3 | 273.8 | 156.2 |
| *W DD* | -51% | -59% | -10% | -15% | -22% | -21% | -22% | -23% | -22% | -24% | -22% | -30% |
| *Skew* | -0.59 | -0.52 | 0.76 | 0.94 | 0.25 | 0.59 | 0.13 | 0.24 | 0.16 | 0.28 | 0.07 | 0.19 |
| *Ex Kurt* | 1.90 | 1.37 | 1.21 | 1.78 | 3.43 | 2.09 | 3.21 | 2.08 | 3.26 | 2.15 | 3.58 | 2.15 |
| *Panel B: 1985 - 2000* | | | | | | | | | | | | |
| *Up* | 0.89 | 0.83 | 2.37 | 2.40 | 1.38 | 1.54 | 1.21 | 1.24 | 1.23 | 1.25 | 1.11 | 1.11 |
| *IR* | - | -0.33 | 0.91 | 0.88 | 0.53 | 0.59 | 0.27 | 0.29 | 0.35 | 0.31 | 0.06 | 0.03 |
| *Omega* | 1.14 | 0.92 | 6.62 | 6.38 | 3.70 | 3.79 | 2.76 | 2.74 | 2.93 | 2.79 | 2.37 | 2.23 |
| *Sortino* | 0.47 | 0.40 | 2.06 | 2.08 | 1.09 | 1.22 | 0.89 | 0.91 | 0.92 | 0.92 | 0.78 | 0.77 |
| *Kappa3* | 0.30 | 0.27 | 1.29 | 1.34 | 0.57 | 0.70 | 0.49 | 0.55 | 0.51 | 0.56 | 0.44 | 0.47 |
| *Sharpe* | 0.49 | 0.36 | 1.68 | 1.60 | 1.17 | 1.20 | 0.93 | 0.93 | 0.99 | 0.94 | 0.76 | 0.71 |
| *Std. dev* | 0.23 | 0.24 | 0.15 | 0.16 | 0.16 | 0.17 | 0.16 | 0.17 | 0.16 | 0.17 | 0.16 | 0.17 |
| *Annual R* | 0.22 | 0.19 | 0.37 | 0.38 | 0.30 | 0.32 | 0.26 | 0.27 | 0.27 | 0.27 | 0.23 | 0.23 |
| *Cum Ret* | 21 | 14 | 127 | 142 | 59 | 73 | 36 | 39 | 42 | 40 | 24 | 22 |
| *W DD* | -38% | -59% | -10% | -10% | -22% | -18% | -22% | -23% | -22% | -24% | -22% | -24% |
| *Skew* | -0.56 | -0.46 | 0.88 | 1.14 | -0.02 | 0.57 | -0.05 | 0.31 | -0.08 | 0.32 | -0.05 | 0.32 |
| *Ex Kurt* | 2.20 | 1.50 | 1.50 | 1.69 | 4.81 | 2.45 | 4.55 | 2.51 | 4.40 | 2.43 | 4.62 | 2.60 |
| *Panel C: 2000 - 2015* | | | | | | | | | | | | |
| *Up* | 0.78 | 0.71 | 1.73 | 1.58 | 1.53 | 1.48 | 1.23 | 1.14 | 1.29 | 1.03 | 1.00 | 0.86 |
| *IR* | - | -0.31 | 0.87 | 0.73 | 0.69 | 0.61 | 0.43 | 0.33 | 0.44 | 0.17 | 0.18 | -0.07 |
| *Omega* | 0.76 | 0.57 | 4.04 | 3.99 | 3.23 | 3.18 | 2.22 | 2.05 | 2.39 | 1.75 | 1.74 | 1.19 |
| *Sortino* | 0.34 | 0.26 | 1.39 | 1.26 | 1.17 | 1.13 | 0.85 | 0.77 | 0.91 | 0.66 | 0.64 | 0.47 |
| *Kappa3* | 0.23 | 0.18 | 0.90 | 0.80 | 0.76 | 0.73 | 0.57 | 0.51 | 0.61 | 0.44 | 0.40 | 0.31 |
| *Sharpe* | 0.51 | 0.35 | 1.63 | 1.60 | 1.43 | 1.41 | 1.15 | 1.11 | 1.19 | 0.94 | 0.88 | 0.65 |
| *Std. dev* | 0.20 | 0.21 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.15 | 0.14 |
| *Annual R* | 0.14 | 0.11 | 0.26 | 0.26 | 0.24 | 0.24 | 0.20 | 0.20 | 0.21 | 0.17 | 0.17 | 0.13 |
| *Cum Ret* | 7 | 4 | 37 | 35 | 27 | 28 | 17 | 15 | 17 | 10 | 10 | 6 |
| *W DD* | -51% | -57% | -9% | -15% | -9% | -21% | -16% | -21% | -16% | -23% | -17% | -30% |
| *Skew* | -0.67 | -0.65 | 0.60 | 0.52 | 0.60 | 0.54 | 0.34 | 0.03 | 0.48 | 0.05 | 0.18 | -0.10 |
| *Ex Kurt* | 1.46 | 1.06 | 0.69 | 1.24 | 0.93 | 0.92 | 0.88 | 0.65 | 1.01 | 0.89 | 2.14 | 1.05 |
| *Panel D: 2008* | | | | | | | | | | | | |
| *Up* | 0.519 | 0.451 | 1.884 | 1.774 | 1.286 | 3.180 | 2.744 | Inf | Inf | Inf | 0.324 | 0.227 |
| *IR* | - | -0.205 | 1.539 | 1.415 | 1.021 | 1.313 | 0.700 | 0.787 | 0.988 | 0.730 | 0.213 | 0.057 |
| *Omega* | 0.008 | -0.104 | 4.257 | 5.305 | 3.626 | 14.577 | 8.703 | Inf | Inf | Inf | 0.210 | -0.265 |
| *Sortino* | 0.004 | -0.052 | 1.526 | 1.493 | 1.008 | 2.976 | 2.461 | Inf | Inf | Inf | 0.056 | -0.082 |
| *Kappa3* | 0.003 | -0.039 | 1.032 | 0.964 | 0.616 | 1.752 | 1.596 | Inf | Inf | Inf | 0.035 | -0.053 |
| *Sharpe* | -0.273 | -0.407 | 1.719 | 1.703 | 1.261 | 1.828 | 1.454 | 1.948 | 1.928 | 1.696 | -0.185 | -0.637 |
| *Std. dev* | 0.339 | 0.302 | 0.175 | 0.172 | 0.154 | 0.155 | 0.087 | 0.082 | 0.107 | 0.080 | 0.160 | 0.117 |
| *Annual R* | -0.053 | -0.085 | 0.353 | 0.346 | 0.243 | 0.337 | 0.174 | 0.207 | 0.255 | 0.182 | 0.011 | -0.036 |
| *Cum Ret* | -0.10 | -0.16 | 0.83 | 0.81 | 0.55 | 0.79 | 0.38 | 0.46 | 0.58 | 0.40 | 0.02 | -0.07 |
| *W DD* | -51% | -54% | -8% | -9% | -9% | -4% | -2% | 0% | 0% | 0% | -16% | -14% |
| *Skew* | -0.82 | -0.63 | 0.49 | 0.94 | 0.48 | 1.85 | 1.37 | 2.24 | 2.01 | 2.56 | -1.41 | -2.47 |
| *Ex Kurt* | -0.13 | 0.48 | -0.29 | 1.70 | 1.76 | 2.93 | 0.54 | 4.25 | 3.13 | 5.68 | 7.53 | 7.95 |
| *Panel E: 1990 – 1999* | | | | | | | | | | | | |
| *Up* | 0.84 | 0.77 | 2.00 | 2.37 | 1.89 | 2.01 | 1.39 | 1.28 | 1.41 | 1.26 | 1.35 | 1.27 |
| *IR* | - | -0.26 | 0.90 | 0.97 | 0.59 | 0.73 | 0.20 | 0.26 | 0.26 | 0.25 | 0.20 | 0.24 |
| *Omega* | 0.91 | 0.75 | 5.46 | 6.23 | 4.02 | 4.57 | 2.50 | 2.57 | 2.81 | 2.58 | 2.46 | 2.53 |
| *Sortino* | 0.40 | 0.33 | 1.69 | 2.04 | 1.51 | 1.65 | 1.00 | 0.92 | 1.04 | 0.91 | 0.96 | 0.91 |
| *Kappa3* | 0.26 | 0.22 | 1.06 | 1.31 | 1.04 | 1.08 | 0.70 | 0.60 | 0.71 | 0.60 | 0.66 | 0.59 |
| *Sharpe* | 0.43 | 0.31 | 1.70 | 1.68 | 1.42 | 1.46 | 0.96 | 0.94 | 1.05 | 0.93 | 0.93 | 0.91 |
| *Std. dev* | 0.23 | 0.24 | 0.14 | 0.16 | 0.14 | 0.16 | 0.14 | 0.15 | 0.14 | 0.15 | 0.14 | 0.15 |
| *Annual R* | 0.18 | 0.16 | 0.33 | 0.36 | 0.29 | 0.32 | 0.22 | 0.23 | 0.23 | 0.23 | 0.22 | 0.23 |
| *Cum Ret* | 4.4 | 3.3 | 16.7 | 20.9 | 11.3 | 15.1 | 6.2 | 7.0 | 6.9 | 6.9 | 6.2 | 6.8 |
| *W DD* | -38% | -59% | -10% | -8% | -9% | -10% | -11% | -23% | -17% | -24% | -17% | -24% |
| *Skew* | -0.55 | -0.57 | -1.71 | -0.77 | 0.63 | -0.17 | -0.94 | -0.39 | -0.47 | -0.16 | 0.87 | 0.12 |
| *Ex Kurt* | 1.96 | 1.59 | 15.65 | 10.17 | 5.95 | 7.07 | 9.99 | 7.50 | 6.79 | 9.60 | 6.13 | 8.55 |
| *Panel F: 2000 - 2009* | | | | | | | | | | | | |
| *Up* | 0.85 | 0.77 | 1.82 | 1.60 | 1.61 | 1.51 | 1.59 | 1.42 | 1.67 | 1.33 | 1.10 | 0.93 |
| *IR* | - | -0.38 | 1.01 | 0.76 | 0.74 | 0.59 | 0.57 | 0.42 | 0.62 | 0.28 | 0.15 | -0.16 |
| *Omega* | 0.87 | 0.64 | 3.74 | 3.33 | 3.19 | 2.86 | 3.14 | 2.71 | 3.45 | 2.47 | 2.07 | 1.32 |
| *Sortino* | 0.39 | 0.30 | 1.43 | 1.23 | 1.22 | 1.12 | 1.20 | 1.04 | 1.29 | 0.95 | 0.74 | 0.53 |
| *Kappa3* | 0.27 | 0.21 | 0.98 | 0.84 | 0.83 | 0.77 | 0.83 | 0.71 | 0.88 | 0.65 | 0.46 | 0.36 |
| *Sharpe* | 0.58 | 0.39 | 1.65 | 1.55 | 1.49 | 1.38 | 1.42 | 1.32 | 1.47 | 1.18 | 0.95 | 0.66 |
| *Std. dev* | 0.23 | 0.24 | 0.17 | 0.17 | 0.17 | 0.17 | 0.16 | 0.16 | 0.16 | 0.16 | 0.17 | 0.17 |
| *Annual R* | 0.19 | 0.14 | 0.34 | 0.32 | 0.30 | 0.29 | 0.28 | 0.27 | 0.29 | 0.24 | 0.21 | 0.16 |
| *Cum Ret* | 4.6 | 2.8 | 17.3 | 15.0 | 13.2 | 12.1 | 11.0 | 9.6 | 11.7 | 7.7 | 5.9 | 3.4 |
| *W DD* | -51% | -57% | -9% | -15% | -9% | -21% | -9% | -21% | -9% | -23% | -17% | -30% |
| *Skew* | -0.60 | -0.50 | 0.59 | 0.51 | 0.56 | 0.55 | 0.66 | 0.45 | 0.74 | 0.53 | 0.40 | 0.33 |
| *Ex Kurt* | 1.16 | 0.66 | 0.50 | 0.72 | 0.88 | 0.62 | 1.15 | 0.85 | 1.17 | 1.09 | 2.27 | 1.41 |

### 5.2.2 Sector Portfolios

Comparing the results from figure 6a and b, the big picture result is the same as the general conclusion from the preceding section; an increased return and decrease in risk with the application of time-series momentum. Figure 6 indicates that the application of time-series momentum indiscriminately have a beneficial effect on all sector portfolios. Comparing Figure 6c and d, we see a notable reduction in risk using the time-series overlay. Except for the Materials telecom and utilities sector, figure 6e exhibits a universal improvement in risk-adjusted performance with the addition of a time-series overlay using a j*=12 month look-back period. From figure 6f we note a substantial improvement in performance during all periods, especially the financial crisis (2008). This relationship is less pronounced for the shorter periods in figure 6g. The Performance Measures in Table 6 below presents the performance measures of both the BHS portfolios and a set of sector portfolio using different time-series look-back periods. Overall the time-series overlay clearly outperforms a BHS on all performance measures. Having already investigated different j* look back periods, we observe (confirm) J*=3 to exhibit relatively better performance globally than the other look back periods.

***Figure 6: Time-Series compared to Buy & Hold Sector Portfolios Illustrations***

Figure 6a and 6c show the cumulative log growth and rolling drawdowns for each sector portfolio with a time-series (TSS) overlay using a j*=12 month look-back period. Figure 6b and 6d show the cumulative log growth and rolling drawdowns for buy & hold sector (BHS) portfolio. It is assumed that NOK 1 was invested January 1985 to December 2015. The box plot figures in Figure 6e show the Sharpe-ratio for the ten TSS sector portfolios using a fixed j*=12 month look-back period and the ten buy and hold sector portfolios (BHS). Each box contains statistical information for the Sharpe ratio over the entire sample period as well as all sub-sample periods. Outliers are represented with dots outside the box. Figure 6f and g show the Sharpe-ratio pattern for the ten TSS sector portfolios using a fixed j*=12 month look-back period and the ten buy and hold sector portfolios (BHS) during the entire as well as all sub sample periods.

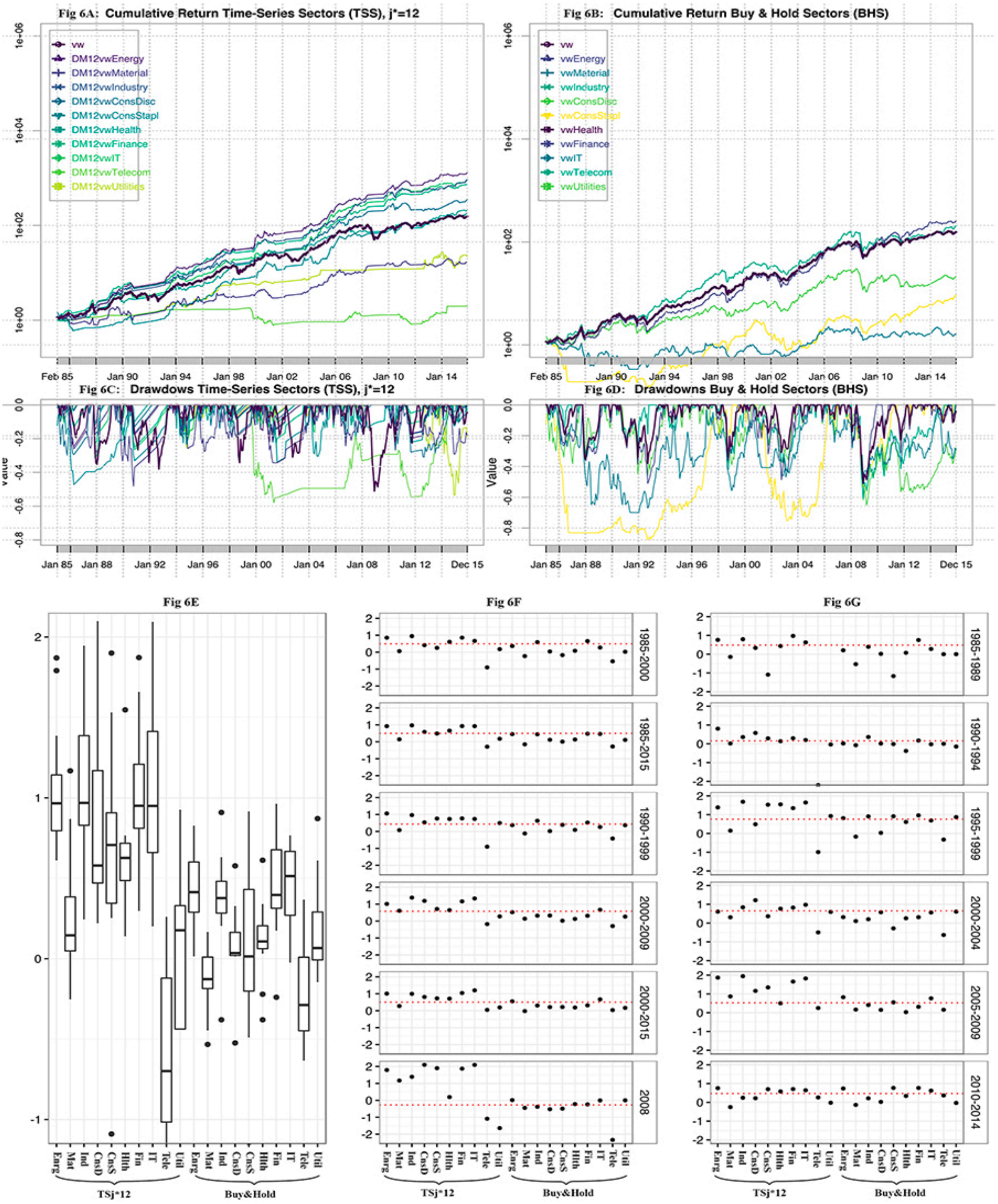


***Table 6: Comparing Performance Measures TSS and BHS from Period 1985 – 2015.***

This table show the performance measures and descriptive statistics over the entire sample period, 1985 – 2015 for the buy and hold sector portfolios (BHS) (Panel A), and the time-series sector (TSS) portfolios using look-back periods of j* = 3, 6, 9, 12 and 16 (Panel B – F)

| LB12 → | Enrg | Mat | Ind | CnsD | CnsS | Hlth | Fin | IT | Tele | Util | Enrg | Mat | Ind | CnsD | CnsS | Hlth | Fin | IT | Tele | Util |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Buy and Hold* | | | | | | | | | | | *Panel D: TS9* | | | | | | | | | |
| *Up Pot* | 0.75 | 0.63 | 0.71 | 0.74 | 0.63 | 0.70 | 0.80 | 0.81 | 0.32 | 0.61 | 1.22 | 0.65 | 1.11 | 0.91 | 0.88 | 0.99 | 1.15 | 1.05 | 0.39 | 0.65 |
| *Inf Ratio* | -0.36 | -0.52 | -0.42 | -0.25 | -0.35 | -0.26 | -0.12 | -0.07 | -0.66 | -0.31 | 0.47 | -0.37 | 0.23 | 0.06 | 0.11 | 0.07 | 0.38 | 0.38 | -0.57 | -0.24 |
| *Omega* | 0.59 | 0.28 | 0.58 | 0.47 | 0.47 | 0.53 | 0.77 | 0.81 | 0.26 | 0.93 | 2.33 | 0.59 | 1.91 | 1.24 | 1.59 | 1.60 | 2.44 | 2.23 | 0.65 | 1.53 |
| *Sortino* | 0.28 | 0.14 | 0.26 | 0.24 | 0.20 | 0.24 | 0.35 | 0.36 | 0.06 | 0.30 | 0.85 | 0.24 | 0.73 | 0.50 | 0.54 | 0.61 | 0.81 | 0.73 | 0.15 | 0.39 |
| *Kappa3* | 0.19 | 0.10 | 0.18 | 0.17 | 0.13 | 0.17 | 0.24 | 0.24 | 0.04 | 0.17 | 0.56 | 0.16 | 0.48 | 0.35 | 0.35 | 0.40 | 0.48 | 0.40 | 0.09 | 0.21 |
| *Sharpe* | 0.23 | -0.06 | 0.19 | 0.14 | 0.09 | 0.13 | 0.38 | 0.41 | -0.28 | 0.11 | 0.96 | 0.11 | 0.83 | 0.52 | 0.62 | 0.62 | 0.96 | 0.93 | -0.18 | 0.22 |
| *Std. dev* | 0.25 | 0.30 | 0.24 | 0.35 | 0.31 | 0.32 | 0.24 | 0.24 | 0.20 | 0.22 | 0.20 | 0.23 | 0.18 | 0.23 | 0.21 | 0.20 | 0.18 | 0.19 | 0.15 | 0.20 |
| *Annual R* | 0.13 | 0.05 | 0.11 | 0.12 | 0.10 | 0.11 | 0.16 | 0.17 | 0.01 | 0.09 | 0.27 | 0.09 | 0.22 | 0.19 | 0.21 | 0.20 | 0.25 | 0.25 | 0.04 | 0.11 |
| *Cum Ret* | 40 | 3 | 27 | 32 | 16 | 25 | 107 | 130 | 0 | 14 | 1578 | 15 | 511 | 238 | 330 | 253 | 1004 | 1030 | 2 | 26 |
| *W DD* | -65% | -83% | -58% | -79% | -86% | -75% | -62% | -61% | -66% | -56% | -22% | -48% | -26% | -30% | -39% | -24% | -23% | -31% | -58% | -42% |
| *Skew* | 0.03 | 0.39 | -0.12 | 0.40 | -0.19 | 1.02 | -0.29 | -0.34 | 3.35 | 2.35 | 1.6 | 0.6 | 0.6 | 1.4 | 0.7 | 1.0 | 0.6 | -0.1 | 1.9 | 2.9 |
| *Ex Kurt* | 2.84 | 3.18 | 1.92 | 1.84 | 4.62 | 5.42 | 0.94 | 1.19 | 43.05 | 16.71 | 11.2 | 5.1 | 2.2 | 8.1 | 4.4 | 4.1 | 4.6 | 4.6 | 31.2 | 25.9 |
| *Panel B: TS3* | | | | | | | | | | | *Panel E: TS12* | | | | | | | | | |
| *Up Pot* | 1.66 | 0.80 | 1.50 | 1.08 | 0.75 | 1.14 | 1.58 | 1.73 | 0.48 | 0.73 | 1.19 | 0.67 | 1.22 | 0.94 | 0.80 | 1.01 | 1.13 | 1.04 | 0.35 | 0.61 |
| *Inf Ratio* | 0.88 | 0.00 | 0.62 | 0.33 | 0.22 | 0.27 | 0.75 | 0.88 | -0.46 | -0.14 | 0.43 | -0.33 | 0.36 | 0.13 | -0.01 | 0.07 | 0.34 | 0.37 | -0.64 | -0.26 |
| *Omega* | 4.17 | 1.25 | 3.22 | 1.86 | 1.87 | 2.10 | 3.97 | 4.21 | 1.19 | 1.94 | 2.29 | 0.63 | 2.28 | 1.43 | 1.29 | 1.74 | 2.40 | 2.24 | 0.42 | 1.32 |
| *Sortino* | 1.34 | 0.45 | 1.14 | 0.70 | 0.49 | 0.78 | 1.26 | 1.40 | 0.26 | 0.48 | 0.83 | 0.26 | 0.85 | 0.55 | 0.45 | 0.64 | 0.79 | 0.72 | 0.10 | 0.35 |
| *Kappa3* | 0.85 | 0.26 | 0.75 | 0.47 | 0.26 | 0.51 | 0.79 | 0.88 | 0.15 | 0.26 | 0.55 | 0.17 | 0.55 | 0.38 | 0.29 | 0.42 | 0.47 | 0.40 | 0.06 | 0.19 |
| *Sharpe* | 1.39 | 0.48 | 1.26 | 0.78 | 0.68 | 0.77 | 1.35 | 1.44 | -0.03 | 0.33 | 0.92 | 0.14 | 0.97 | 0.58 | 0.49 | 0.66 | 0.93 | 0.93 | -0.29 | 0.18 |
| *Std. dev* | 0.19 | 0.22 | 0.17 | 0.23 | 0.24 | 0.22 | 0.18 | 0.18 | 0.17 | 0.21 | 0.20 | 0.23 | 0.18 | 0.23 | 0.22 | 0.19 | 0.18 | 0.19 | 0.14 | 0.21 |
| *Annual R* | 0.35 | 0.18 | 0.30 | 0.25 | 0.24 | 0.25 | 0.32 | 0.35 | 0.06 | 0.14 | 0.26 | 0.10 | 0.25 | 0.21 | 0.18 | 0.20 | 0.24 | 0.25 | 0.02 | 0.11 |
| *Cum Ret* | 9862 | 165 | 3274 | 1089 | 735 | 902 | 5512 | 10079 | 5 | 55 | 1298 | 19 | 967 | 347 | 160 | 257 | 821 | 999 | 1 | 21 |
| *W DD* | -15% | -48% | -15% | -39% | -63% | -29% | -20% | -18% | -32% | -36% | -25% | -48% | -26% | -31% | -47% | -24% | -25% | -31% | -58% | -53% |
| *Skew* | 2.0 | 0.4 | 0.8 | 1.5 | -0.8 | 1.5 | 1.2 | 0.9 | 5.9 | 2.9 | 1.6 | 0.6 | 0.6 | 1.6 | 0.6 | 0.9 | 0.7 | -0.1 | 1.9 | 2.7 |
| *Ex Kurt* | 12.7 | 7.3 | 1.8 | 8.1 | 11.2 | 5.0 | 4.2 | 1.4 | 66.2 | 21.6 | 11.1 | 4.7 | 2.2 | 8.9 | 4.3 | 3.3 | 4.9 | 4.6 | 34.8 | 22.0 |
| *Panel C: TS6* | | | | | | | | | | | *Panel F: TS16* | | | | | | | | | |
| *Up Pot* | 1.52 | 0.63 | 1.28 | 1.01 | 0.99 | 1.15 | 1.29 | 1.23 | 0.42 | 0.69 | 1.04 | 0.53 | 1.00 | 0.83 | 0.75 | 0.93 | 0.91 | 0.93 | 0.47 | 0.58 |
| *Inf Ratio* | 0.74 | -0.29 | 0.43 | 0.21 | 0.30 | 0.24 | 0.61 | 0.66 | -0.51 | -0.19 | 0.20 | -0.55 | 0.14 | -0.11 | -0.10 | -0.04 | 0.04 | 0.16 | -0.54 | -0.31 |
| *Omega* | 3.41 | 0.74 | 2.48 | 1.50 | 2.19 | 2.13 | 3.10 | 3.03 | 0.96 | 1.63 | 1.80 | 0.34 | 1.80 | 1.04 | 1.11 | 1.45 | 1.65 | 1.83 | 0.92 | 1.10 |
| *Sortino* | 1.17 | 0.27 | 0.91 | 0.61 | 0.68 | 0.79 | 0.98 | 0.92 | 0.21 | 0.43 | 0.67 | 0.14 | 0.65 | 0.42 | 0.40 | 0.55 | 0.56 | 0.60 | 0.22 | 0.30 |
| *Kappa3* | 0.74 | 0.16 | 0.59 | 0.42 | 0.42 | 0.51 | 0.57 | 0.49 | 0.11 | 0.23 | 0.44 | 0.09 | 0.40 | 0.29 | 0.26 | 0.36 | 0.35 | 0.34 | 0.13 | 0.17 |
| *Sharpe* | 1.23 | 0.19 | 1.04 | 0.65 | 0.83 | 0.81 | 1.14 | 1.16 | -0.09 | 0.28 | 0.72 | -0.08 | 0.75 | 0.39 | 0.40 | 0.54 | 0.63 | 0.73 | -0.12 | 0.12 |
| *Std. dev* | 0.19 | 0.23 | 0.18 | 0.23 | 0.21 | 0.20 | 0.19 | 0.20 | 0.14 | 0.20 | 0.20 | 0.24 | 0.18 | 0.22 | 0.21 | 0.18 | 0.18 | 0.19 | 0.13 | 0.21 |
| *Annual R* | 0.32 | 0.11 | 0.26 | 0.23 | 0.25 | 0.24 | 0.29 | 0.31 | 0.05 | 0.13 | 0.22 | 0.05 | 0.21 | 0.16 | 0.16 | 0.17 | 0.19 | 0.21 | 0.05 | 0.09 |
| *Cum Ret* | 5217 | 26 | 1322 | 561 | 1025 | 710 | 2803 | 3816 | 4 | 39 | 451 | 3 | 339 | 90 | 93 | 130 | 201 | 377 | 3 | 14 |
| *W DD* | -22% | -55% | -18% | -39% | -37% | -19% | -26% | -31% | -53% | -47% | -26% | -69% | -29% | -30% | -47% | -30% | -32% | -31% | -45% | -56% |
| *Skew* | 1.9 | 0.0 | 0.7 | 1.4 | 0.7 | 1.2 | 0.8 | 0.2 | 2.0 | 2.8 | 1.6 | -0.2 | 0.3 | 1.5 | 0.4 | 0.9 | 0.5 | -0.1 | 3.4 | 2.7 |
| *Ex Kurt* | 12.2 | 7.8 | 2.3 | 7.5 | 4.6 | 3.7 | 4.8 | 4.2 | 32.7 | 22.6 | 11.5 | 5.5 | 3.4 | 9.9 | 4.1 | 3.3 | 5.2 | 4.8 | 38.5 | 22.7 |

### 5.2.3 Dual – Momentum

From 7a, we see that the addition of a time-series overlay using a j*=12-month look back period to the pure XSI-MOMj12 lifts the performance of most portfolios above the benchmark. Figure 7c illustrates a substantial overall decrease in drawdown profile relative to the benchmark (compare with figure 3c).

Comparing the DMI strategies in figure 7a with the XSS-MOM strategies in figure 4e, we see that the for the latter, P1 – P4 have a cumulative return curve with a marked decrease in risk and drawdown profile. The sectors with a prior poor performance fail to beat the benchmark even with the inclusion of the time-series overlay. This finding is in contrast to the DMI portfolios, where all portfolios show a moderate outperformance or at par with the benchmark with the inclusion of the time-series overlay. For the DMS strategies in fig 7e, P1-P4 exhibits a substantially better profile than the P2-P5 for the DMI (fig 7a) portfolio strategies. This finding presents the possibility that the very extreme performance of the figure 7a, P1 stocks in the DMI strategy are "spread" across the sector portfolios P1-P4.

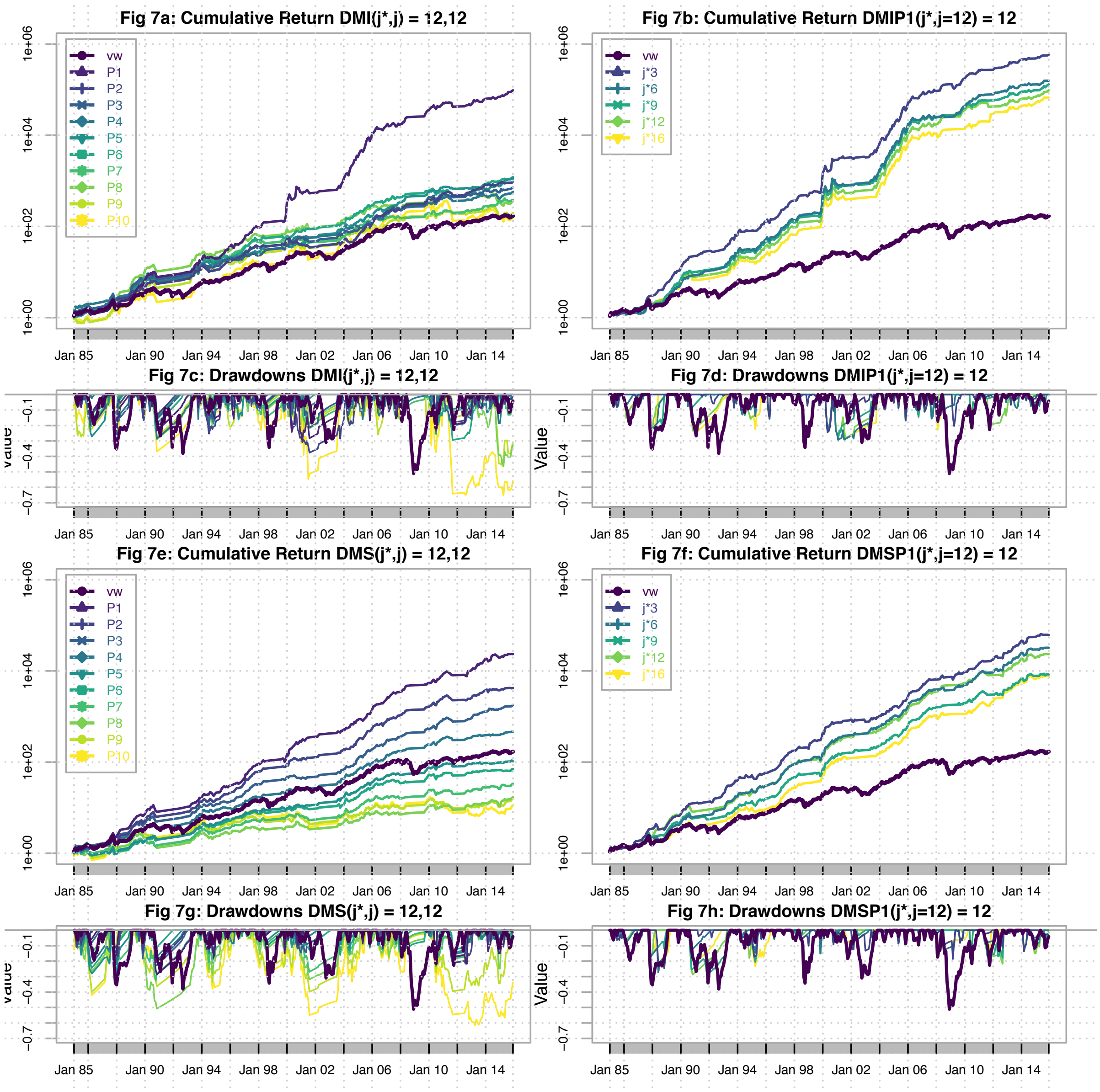
With the addition of j* = 3 look-back period, all portfolios outperform the benchmark during all periods in figure 7a, b and c. The look-back periods j*=6,9 and 12 also exhibit very robust performance where in general the shorter periods appears to work the best. Note that substantial benefit of adding the time-series strategy compared to the pure XSI-MOM strategy (fig 4), during the financial crisis. The longer time-series look back period j*16 only slightly add value compared to the pure XSI-MOM strategy and only modestly increases performance during 2008. The general improved performance is also apparent in figure 7c. However, the longer time-frames show more persistence in results.

Table 7a presents additional information on the performance and descriptive statistics. Compared to the pure XSI-MOM strategy, all portfolios exhibit significantly more right tailed distribution of returns (Skewness) by avoiding downturn markets. We note that P1 with the additional time-series overlay outperform P1 on the pure XSI-MOM strategy on all the selected performance measures; worth highlighting is the P1 DMI worst drawdown of 29% compared to P1 XSI-MOM of 62%.

For the DMS portfolios in figure 7d,e and f, we see that the addition of a time-series overlay to the cross-sectional sector momentum strategies appears to universally enhance risk adjusted performance. We observe that the predictable return pattern (P1 best, P10 worst) of pure Cross-sectional sector momentum (XSS-MOM table 4d, e and f) largely remain intact for j*=3,6,9 and 12. Looking at figure 7 the general results largely points to the same results as for the DMI strategies where the time-series overlay exhibit a robust over-performance relative to the pure cross-sectional strategies and benchmark.

***Figure 7: Dual Momentum Individual Stocks and Sectors***

Figure 7a and 7c (7e and 7g) show the cumulative log returns and drawdowns for each DMI (DMS) decile portfolio using a j*=12-month time-series look-back period. Fig 7b and 7d (7f and 7h) show the cumulative log returns and drawdowns for DMI (DMS) P1 using a set of different time-series j*, look-back periods. It is assumed that NOK 1 was invested January 1985 to December 2015. The bold line represents the benchmark portfolio (vw).



### *Figure 8: Robustness Dual-Momentum*

The box plot figures in Fig 8a (8d) show the Sharpe-ratio for the each Dual Momentum P1-P10 (column 1-10), using a fixed cross sectional look back period j = 12 and a set of different look back periods from j* = 3,6,9,12,16 for the time-series overlay. I contains statistical information for the Sharpe ratio over the entire sample period as well as all sub-sample periods, i.e., a total of n =12 observations, described in chapter 3 section 2. Outliers are represented with dots outside the box. Fig 8b (8e) show the Sharpe-ratio pattern for the each P1-P10 using a fixed cross sectional look back period j = 12 and a set of different look back periods from j* = 3,6,9,12,16 for the time-series overlay during the sample periods 1985-2015, 1985 – 2000, 2000-2015, 2008 (the financial crisis), 1990-1999 and 2000 – 2009 (row 1-6 respectively). Fig 8c (8f) show the Sharpe-ratio pattern for the time-series overlay during a set of five-year sample periods 1985-1989, 1990 – 1994, 1995 – 1999, 2000 – 2004, 2005 – 2009, 2010 – 2014 (row 1-6 respectively).

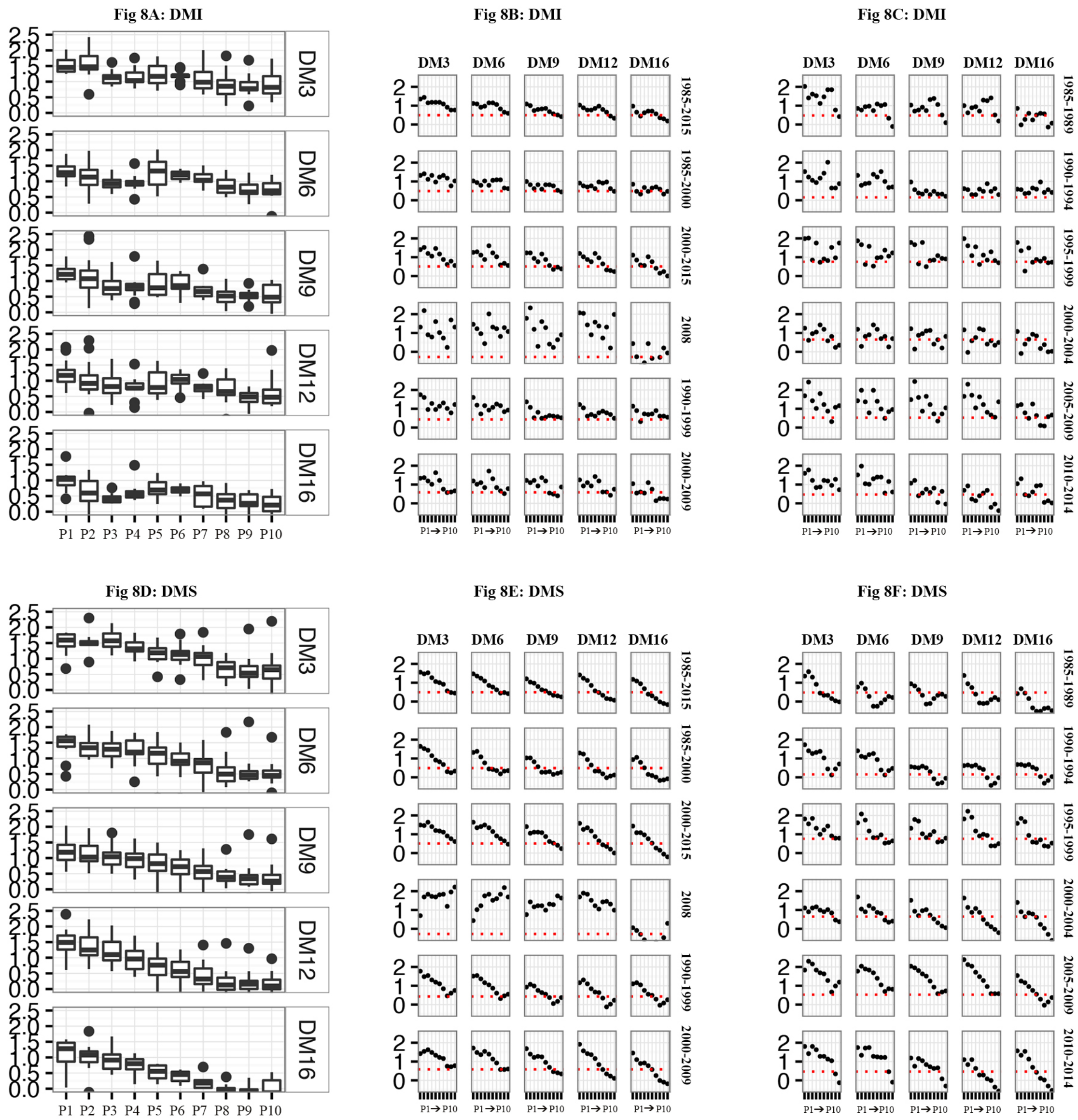


*Table 7: Performance measures Dual momentum Individual stocks (DMI) 1985 – 2015*

**Table 7a: DMI Performance Measures**

This table shows the performance measures and descriptive statistics over the entire sample period 1985 – 2015 for all DMI portfolios P1-P10 using a j = 12 month cross-sectional look back period and a j* = 12 month look-back period in the time-series overlay.

| XSI, J*=12, j=12 → | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Upside potential | 1.38 | 1.04 | 1.01 | 1.01 | 1.17 | 1.13 | 1.01 | 0.95 | 0.83 | 0.71 |
| Information Ratio | 0.88 | 0.34 | 0.27 | 0.25 | 0.36 | 0.37 | 0.16 | 0.14 | 0.02 | 0.00 |
| Omega ratio | 3.00 | 2.01 | 1.79 | 1.88 | 2.03 | 2.24 | 1.78 | 1.51 | 1.13 | 0.85 |
| Sortino ratio | 1.04 | 0.70 | 0.64 | 0.66 | 0.79 | 0.78 | 0.65 | 0.57 | 0.44 | 0.33 |
| Kappa3 ratio | 0.66 | 0.44 | 0.40 | 0.41 | 0.51 | 0.51 | 0.40 | 0.37 | 0.29 | 0.21 |
| Sharpe ratio | 1.04 | 0.87 | 0.77 | 0.75 | 0.85 | 0.95 | 0.78 | 0.64 | 0.45 | 0.32 |
| Standard deviation | 0.35 | 0.20 | 0.21 | 0.20 | 0.21 | 0.19 | 0.18 | 0.21 | 0.25 | 0.33 |
| Annualized return | 0.45 | 0.25 | 0.24 | 0.23 | 0.26 | 0.25 | 0.21 | 0.21 | 0.19 | 0.18 |
| Cumulative return | 96832 | 961 | 717 | 575 | 1197 | 1096 | 378 | 357 | 195 | 162 |
| Worst drawdown | -29% | -38% | -27% | -29% | -27% | -29% | -24% | -47% | -46% | -65% |
| Skewness | 4.18 | 0.21 | 0.71 | 1.01 | 1.33 | 0.57 | 0.12 | 0.59 | 0.82 | 0.35 |
| Excess Kurtosis | 37.52 | 1.85 | 4.94 | 5.87 | 5.83 | 2.92 | 2.49 | 2.58 | 3.60 | 3.54 |

**Table 7b: DMS Performance Measures**

This table shows the performance measures and descriptive statistics over the entire sample period 1985 – 2015 for all DMS portfolios P1-P10 using a j = 12 month cross-sectional look back period and a j* = 12 month look-back period in the time-series overlay.

| DMS, J*=12, j=12 → | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 | P9 | P10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Upside potential | 1.53 | 1.40 | 1.30 | 1.07 | 0.82 | 0.82 | 0.75 | 0.68 | 0.72 | 0.68 |
| Information Ratio | 0.99 | 0.65 | 0.49 | 0.22 | -0.11 | -0.18 | -0.32 | -0.40 | -0.39 | -0.39 |
| Omega ratio | 3.76 | 3.22 | 3.13 | 2.37 | 1.56 | 1.40 | 0.99 | 0.66 | 0.57 | 0.44 |
| Sortino ratio | 1.21 | 1.07 | 0.99 | 0.75 | 0.50 | 0.48 | 0.37 | 0.27 | 0.26 | 0.21 |
| Kappa3 ratio | 0.74 | 0.67 | 0.58 | 0.43 | 0.29 | 0.29 | 0.24 | 0.18 | 0.19 | 0.15 |
| Sharpe ratio | 1.42 | 1.23 | 1.11 | 0.85 | 0.56 | 0.48 | 0.31 | 0.15 | 0.13 | 0.06 |
| Standard deviation | 0.21 | 0.19 | 0.18 | 0.17 | 0.16 | 0.16 | 0.16 | 0.19 | 0.21 | 0.25 |
| Annualized return | 0.38 | 0.31 | 0.27 | 0.22 | 0.16 | 0.15 | 0.12 | 0.10 | 0.09 | 0.08 |
| Cumulative return | 23370 | 4230 | 1793 | 463 | 103 | 70 | 33 | 16 | 15 | 10 |
| Worst drawdown | -29% | -22% | -23% | -23% | -29% | -24% | -33% | -51% | -40% | -62% |
| Skewness | 1.03 | 0.76 | 0.93 | 0.72 | -0.41 | 0.05 | -0.12 | 0.33 | 0.52 | 0.40 |
| Excess Kurtosis | 4.20 | 2.49 | 4.70 | 6.43 | 5.70 | 3.74 | 3.21 | 3.32 | 1.64 | 1.46 |

## 5.3 Regression Analysis

Table 8a presents the factor regression results for the XSI-MOM portfolios. In addition to the market being a highly significant loading for all portfolios, the book to market factor - HML is significant negative loading for P1, i.e., negative relation to growth. P1 is able to deliver substantial significant alpha, capturing a significant momentum, PR1YR factor loading. For all other portfolios we have non-significant alpha values. Table 8b presents the factor regression results for the XSS-MOM portfolios. The market is a highly significant factor loading for all portfolios. P1 show weak but significant negative SMB factor loading, i.e., indicating a concentration of larger firms clustered in the top-performing sector; as the OSE historically have been and to a lesser extent still is highly concentrated of a few large firms, this finding is to be expected. P1 exhibit a strong significant alpha in addition to a weak but significant positive liquidity, LIQ factor loading. We also observe a significant alpha for P2 — confirming the observation from figure 4, and 5, where trading the second best performing portfolio over the prior j months, is able to deliver systematic alpha. P3 also exhibit a weak but significant alpha. Portfolio 5-9 all have a negative alpha value, indicating a relative underperformance in these portfolios relative to the value-weighted benchmark portfolio. The latter observation is also consistent with the inverted or slightly convex risk-adjusted performance profile seen in figure 5d, e and f. A final observation from the XSS-MOM regression in table 9b is that neither P1, P2 or P3 the momentum factor, PR1YR, is non-significant, unlike XSS-MOM, P1 in table 9a.

Table 9a show the results from the application of time-series momentum to the market portfolios, indicating the prior observations from the analysis in section 5.2 with respect to time-series momentum —highly significant alpha values for all market portfolios with a time-series overlay. The t-values diminish for j*>3. Value-weighted portfolios exhibit greater significance, albeit both highly significant. No risk factors at the OSE can presently explain the time-series momentum returns applied to market portfolios. 9b, we see that the inclusion of the time-series overlay to XSI-MOM results in substantially significant alpha values for P1-P8, and weaker significance for P9 and non-significant alpha for P10. We note the decrease in $R^2$ and that smaller factors loadings to the market portfolio (albeit still are highly significant but smaller than for the pure cross-sectional strategies); consistent with being positioned in the generally uncorrelated risk free rate, N3M. From table 9c, we see that the inclusion of the time-series overlay to the cross-sectional sector portfolio strategies results in substantially significant alpha values for P1-P4. Compared to the significantly negative alpha values for P5 – P9 from the XSS-MOM factor regressions, the results from table 10c now exhibit non-significant alpha values for these portfolios.

*Table 8: XSI-MOM Factor Regressions 1985 – 2015.*

**Table 8a: XSI-MOM Factor Regressions 1985 – 2015.**

This table presents the resulting beta values and t-statistics from the multi-factor time-series regressions of cross-sectional stock (XSI-MOM) momentum strategies regressed on the returns of the vw, SMB, HML, PR1YR and LIQ return series, all decile Portfolios using a j = 12 look-back period.

| Portfolio | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| vw | 1.276 | 0.946 | 0.939 | 0.974 | 1.008 | 0.997 | 1.043 | 1.169 | 1.128 | 1.294 |
| | t = 18.35$^{***}$ | t = 23.14$^{***}$ | t = 22.37$^{***}$ | t = 26.98$^{***}$ | t = 23.67$^{***}$ | t = 24.46$^{***}$ | t = 24.39$^{***}$ | t = 25.56$^{***}$ | t = 16.82$^{***}$ | t = 13.68$^{***}$ |
| SMB | 0.121 | 0.071 | 0.062 | 0.046 | -0.015 | -0.045 | -0.016 | -0.134 | 0.219 | 0.193 |
| | t = 0.913 | t = 0.911 | t = 0.771 | t = 0.672 | t = -0.182 | t = -0.583 | t = -0.197 | t = -1.542 | t = 1.709$^{*}$ | t = 1.072 |
| HML | -0.211 | 0.021 | 0.055 | -0.072 | 0.049 | 0.053 | 0.093 | 0.087 | 0.102 | 0.089 |
| | t = -2.289$^{**}$ | t = 0.380 | t = 0.979 | t = -1.508 | t = 0.860 | t = 0.976 | t = 1.633 | t = 1.437 | t = 1.142 | t = 0.707 |
| PR1YR | 0.236 | 0.065 | -0.037 | -0.011 | -0.012 | -0.048 | -0.150 | -0.068 | -0.130 | -0.110 |
| | t = 2.623$^{***}$ | t = 1.226 | t = -0.688 | t = -0.238 | t = -0.223 | t = -0.917 | t = -2.719$^{***}$ | t = -1.144 | t = -1.496 | t = -0.896 |
| LIQ | 0.037 | -0.030 | -0.064 | 0.048 | 0.038 | 0.010 | 0.029 | -0.010 | -0.145 | 0.084 |
| | t = 0.318 | t = -0.435 | t = -0.916 | t = 0.789 | t = 0.525 | t = 0.144 | t = 0.409 | t = -0.124 | t = -1.290 | t = 0.528 |
| Alpha | 0.013 | 0.0001 | 0.0001 | 0.0004 | 0.002 | -0.001 | 0.001 | -0.005 | -0.003 | 0.0002 |
| | t = 2.847$^{***}$ | t = 0.045 | t = 0.047 | t = 0.184 | t = 0.724 | t = -0.342 | t = 0.276 | t = -1.619 | t = -0.771 | t = 0.039 |
| Adjusted $R^2$ | 0.496 | 0.604 | 0.586 | 0.672 | 0.611 | 0.625 | 0.629 | 0.644 | 0.451 | 0.353 |

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

**Table 8b: XSS-MOM Factor Regressions**

This table presents the resulting beta values and t-statistics from the multi-factor time-series regressions of cross-sectional stock (XSS-MOM) momentum strategies regressed on the returns of the vw, SMB, HML, PR1YR and LIQ return series, all decile Portfolios using a j = 12 look-back period.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| vw | 1.018 | 0.890 | 0.870 | 0.946 | 0.927 | 0.880 | 0.852 | 0.849 | 0.949 | 1.025 |
| | t = 22.61$^{***}$ | t = 22.17$^{***}$ | t = 25.57$^{***}$ | t = 33.57$^{***}$ | t = 34.07$^{***}$ | t = 29.23$^{***}$ | t = 24.48$^{***}$ | t = 18.28$^{***}$ | t = 17.14$^{***}$ | t = 15.09$^{***}$ |
| SMB | -0.148 | -0.022 | 0.032 | -0.017 | -0.001 | 0.098 | 0.126 | 0.024 | -0.042 | 0.017 |
| | t = -1.725$^{*}$ | t = -0.285 | t = 0.498 | t = -0.319 | t = -0.021 | t = 1.712$^{*}$ | t = 1.894$^{*}$ | t = 0.270 | t = -0.396 | t = 0.130 |
| HML | 0.090 | 0.011 | 0.025 | 0.034 | 0.028 | 0.034 | 0.051 | 0.016 | 0.004 | 0.031 |
| | t = 1.499 | t = 0.200 | t = 0.548 | t = 0.904 | t = 0.789 | t = 0.860 | t = 1.109 | t = 0.259 | t = 0.060 | t = 0.348 |
| PR1YR | -0.013 | -0.047 | -0.041 | 0.012 | -0.016 | -0.037 | 0.007 | 0.004 | -0.068 | -0.133 |
| | t = -0.225 | t = -0.906 | t = -0.928 | t = 0.322 | t = -0.457 | t = -0.943 | t = 0.159 | t = 0.060 | t = -0.954 | t = -1.510 |
| LIQ | 0.125 | 0.096 | 0.025 | 0.010 | -0.021 | -0.076 | -0.118 | -0.117 | -0.126 | -0.182 |
| | t = 1.661$^{*}$ | t = 1.428 | t = 0.441 | t = 0.207 | t = -0.470 | t = -1.498 | t = -2.026$^{**}$ | t = -1.498 | t = -1.356 | t = -1.599 |
| Constant | 0.009 | 0.006 | 0.004 | -0.001 | -0.005 | -0.005 | -0.008 | -0.009 | -0.008 | -0.006 |
| | t = 3.138$^{***}$ | t = 2.349$^{**}$ | t = 1.801$^{*}$ | t = -0.352 | t = -2.628$^{***}$ | t = -2.816$^{***}$ | t = -3.714$^{***}$ | t = -3.187$^{***}$ | t = -2.161$^{**}$ | t = -1.497 |
| Observations | 372 | 372 | 372 | 372 | 372 | 372 | 372 | 372 | 372 | 372 |
| $R^2$ | 0.594 | 0.585 | 0.654 | 0.763 | 0.768 | 0.713 | 0.638 | 0.488 | 0.453 | 0.395 |
| Adjusted $R^2$ | 0.589 | 0.579 | 0.649 | 0.759 | 0.765 | 0.709 | 0.633 | 0.481 | 0.446 | 0.387 |

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

***Table 9: Time-Series Momentum Regressions, 1985 – 2015.***

**Table 9a: Market portfolio Times-Series, TSvw Regression**

Table 10a presents the regression results on the application of Time-series momentum to the market portfolios.

| Portfolio | TS3vw | TS3ew | TS6vw | TS6ew | TS9vw | TS9ew | TS12vw | TS12ew | TS16vw | TS16ew |
|---|---|---|---|---|---|---|---|---|---|---|
| vw | 0.462 | 0.413 | 0.499 | 0.452 | 0.506 | 0.453 | 0.504 | 0.452 | 0.504 | 0.445 |
| | **t = 18.74*** | **t = 14.33*** | **t = 19.47*** | **t = 15.22*** | **t = 19.25*** | **t = 15.37*** | **t = 19.29*** | **t = 15.37*** | **t = 19.02*** | **t = 15.12*** |
| SMB | 0.026 | 0.081 | 0.007 | 0.063 | -0.053 | 0.002 | -0.045 | -0.002 | -0.019 | 0.019 |
| | t = 0.552 | t = 1.48 | t = 0.14 | t = 1.12 | t = -1.06 | t = 0.03 | t = -0.92 | t = -0.04 | t = -0.38 | t = 0.34 |
| HML | -0.034 | -0.012 | -0.015 | 0.019 | -0.011 | 0.023 | -0.028 | -0.001 | -0.062 | -0.030 |
| | t = -1.05 | t = -0.31 | t = -0.45 | t = 0.49 | t = -0.32 | t = 0.59 | t = -0.82 | t = -0.01 | **t = -1.76*** | t = -0.76 |
| PR1YR | -0.048 | -0.038 | -0.025 | -0.036 | 0.020 | 0.007 | 0.039 | 0.033 | 0.039 | 0.037 |
| | t = -1.52 | t = -1.03 | t = -0.75 | t = -0.93 | t = 0.59 | t = 0.19 | t = 1.16 | t = 0.88 | t = 1.13 | t = 0.97 |
| LIQ | 0.046 | 0.042 | 0.017 | 0.013 | 0.060 | 0.057 | 0.066 | 0.080 | 0.046 | 0.071 |
| | t = 1.12 | t = 0.87 | t = 0.40 | t = 0.25 | t = 1.37 | t = 1.16 | t = 1.51 | t = 1.62 | t = 1.03 | t = 1.45 |
| Constant | 0.019 | 0.020 | 0.016 | 0.017 | 0.013 | 0.014 | 0.014 | 0.013 | 0.011 | 0.010 |
| | **t = 12.29*** | **t = 10.65*** | **t = 9.79*** | **t = 8.92*** | **t = 8.00*** | **t = 7.25*** | **t = 8.24*** | **t = 6.73*** | **t = 6.41*** | **t = 5.12*** |
| Adjusted $R^2$ | 0.500 | 0.379 | 0.513 | 0.401 | 0.505 | 0.402 | 0.508 | 0.403 | 0.501 | 0.397 |

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

**Table 9b: DMI Factor Regression**

This table presents the resulting beta values and t-statistics from the multi-factor time-series regressions of cross-sectional stock momentum strategies with an applied time-series overlay (DMI) regressed on the returns of the vw, SMB, HML, PR1YR and LIQ return series, all decile Portfolios using a j = 12 look-back period for the cross-sectional component and a j* = 12 months look back period for the time-series overlay

| Portfolio | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| vw | 0.813 | 0.484 | 0.514 | 0.544 | 0.508 | 0.447 | 0.421 | 0.512 | 0.484 | 0.546 |
| | **t = 11.178*** | **t = 11.775*** | **t = 11.829*** | **t = 13.418*** | **t = 11.370*** | **t = 11.494*** | **t = 11.345*** | **t = 11.624*** | **t = 8.775*** | **t = 7.251*** |
| SMB | 0.083 | 0.009 | 0.039 | -0.021 | -0.040 | -0.016 | -0.018 | -0.152 | 0.050 | 0.140 |
| | t = 0.598 | t = 0.113 | t = 0.476 | t = -0.269 | t = -0.472 | t = -0.218 | t = -0.253 | **t = -1.815*** | t = 0.476 | t = 0.976 |
| HML | -0.224 | 0.055 | 0.059 | -0.067 | 0.008 | 0.022 | -0.009 | 0.042 | -0.008 | 0.082 |
| | **t = -2.324**** | t = 1.007 | t = 1.030 | t = -1.242 | t = 0.129 | t = 0.428 | t = -0.173 | t = 0.712 | t = -0.112 | t = 0.816 |
| PR1YR | 0.209 | 0.046 | -0.020 | 0.007 | 0.039 | 0.001 | -0.057 | 0.025 | -0.016 | 0.057 |
| | **t = 2.227**** | t = 0.858 | t = -0.363 | t = 0.135 | t = 0.679 | t = 0.024 | t = -1.194 | t = 0.438 | t = -0.223 | t = 0.582 |
| LIQ | 0.023 | 0.027 | -0.002 | 0.084 | 0.058 | 0.021 | 0.043 | 0.147 | 0.070 | 0.027 |
| | t = 0.186 | t = 0.388 | t = -0.026 | t = 1.240 | t = 0.776 | t = 0.326 | t = 0.690 | **t = 1.990**** | t = 0.760 | t = 0.216 |
| Constant | 0.020 | 0.009 | 0.009 | 0.008 | 0.010 | 0.010 | 0.008 | 0.008 | 0.006 | 0.006 |
| | **t = 4.302*** | **t = 3.529*** | **t = 3.104*** | **t = 3.107*** | **t = 3.594*** | **t = 4.186*** | **t = 3.450*** | **t = 2.724*** | **t = 1.736*** | t = 1.163 |
| Adjusted $R^2$ | 0.272 | 0.281 | 0.283 | 0.332 | 0.260 | 0.264 | 0.260 | 0.272 | 0.177 | 0.134 |

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

**Table 9c: DMS Factor Regression**

This table presents the resulting beta values and t-statistics from the multi-factor time-series regressions of cross-sectional stock momentum strategies with an applied time-series overlay (DMS) regressed on the returns of the vw, SMB, HML, PR1YR and LIQ return series, all decile Portfolios using a j = 12 look-back period for the cross-sectional component and a j* = 12 months look back

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| vw | 0.530 | 0.452 | 0.442 | 0.474 | 0.449 | 0.420 | 0.405 | 0.427 | 0.462 | 0.477 |
| | **t = 12.16*** | **t = 11.66*** | **t = 12.262*** | **t = 14.327*** | **t = 14.095*** | **t = 12.999*** | **t = 11.938*** | **t = 10.226*** | **t = 10.175*** | **t = 8.575*** |
| SMB | -0.107 | -0.050 | -0.006 | -0.002 | 0.002 | 0.039 | 0.039 | -0.064 | -0.070 | 0.035 |
| | t = -1.290 | t = -0.677 | t = -0.084 | t = -0.034 | t = 0.035 | t = 0.628 | t = 0.604 | t = -0.799 | t = -0.808 | t = 0.325 |
| HML | 0.034 | -0.008 | 0.018 | 0.048 | 0.015 | -0.015 | -0.009 | -0.036 | -0.047 | -0.028 |
| | t = 0.579 | t = -0.159 | t = 0.366 | t = 1.093 | t = 0.358 | t = -0.353 | t = -0.203 | t = -0.643 | t = -0.776 | t = -0.378 |
| PR1YR | 0.069 | 0.026 | 0.027 | 0.051 | 0.028 | 0.003 | 0.035 | 0.034 | 0.006 | 0.005 |
| | t = 1.229 | t = 0.524 | t = 0.587 | t = 1.197 | t = 0.675 | t = 0.077 | t = 0.794 | t = 0.623 | t = 0.098 | t = 0.071 |
| LIQ | 0.123 | 0.149 | 0.110 | 0.049 | 0.010 | -0.003 | -0.037 | -0.018 | -0.016 | -0.071 |
| | **t = 1.683*** | **t = 2.296**** | **t = 1.826*** | t = 0.875 | t = 0.187 | t = -0.048 | t = -0.644 | t = -0.263 | t = -0.212 | t = -0.764 |
| Constant | 0.018 | 0.014 | 0.011 | 0.007 | 0.003 | 0.003 | 0.001 | -0.0004 | -0.0004 | -0.001 |
| | **t = 6.563*** | **t = 5.686*** | **t = 4.921*** | **t = 3.296*** | t = 1.631 | t = 1.242 | t = 0.233 | t = -0.158 | t = -0.134 | t = -0.411 |
| Adjusted $R^2$ | 0.290 | 0.280 | 0.304 | 0.370 | 0.355 | 0.320 | 0.283 | 0.214 | 0.212 | 0.162 |

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

## 5.4 Comparative Analysis and intermediate summary

This section presents a selection of the most relevant salient findings on the basis of the most persistent and robust parameters. That is, having a long position in the top 10 % top performing stocks/sectors over the prior j = 12 months and/or applying a time-series momentum overlay based on if the cumulative excess returns of the value-weighted market portfolio have been positive over the j* 3 and 12 prior months.

From Figure 9 and table 10, I underscore the following:

- The addition of a time-series overlay to a cross-sectional momentum strategy significantly improves return and decrease in overall risk, i.e., Dual-Momentum.
- The addition of a time-series overlay significantly improves risk adjusted returns to an otherwise passively managed market portfolio
- Cross-Sectional individual stock momentum appear highly concentrated in the extreme decile (top 10%). Long-only Cross-Sectional individual stock momentum systematically outperform the market portfolio and is partly explained by the momentum, PR1YR risk factor.
- Cross-sectional sector momentum is Less concentrated than for individual stocks but systematically outperforms the market portfolio. Cross-sectional sector momentum does not appear to be explained by the momentum, PR1YR risk factor.
- Dual momentum outperform time-series momentum applied to the market portfolio given substantially more skewed return profile. Time-series momentum applied to market portfolio give a greater measure in the more conventional Sharpe-Ratio.
- A simple time-series overlay appear to perform better on a risk-adjusted basis than a cross-sectional momentum strategy. (especially considering potential transaction costs)
- Both value and equally weighted momentum portfolios effective.

*__Figure 9: Comparative Analysis__*

Figure 9a (9b) show the cumulative returns for the top performing over the prior j = 12 individual stock (XSI) and sector (XSI) with and without a j* = 12 month time series overlay (DMI and DMS respectively). Further, we have the BHvw (Fig 9a), BHew(Fig 9b) with and without a j*=3 and 12-month time-series overlay. It is assumed that NOK 1 was invested January 1985 to December 2015. Fig show the rolling drawdowns the bolded blue line represents the vw portfolio. Fig9E show the performance of all portfolios relative to TS3vw.

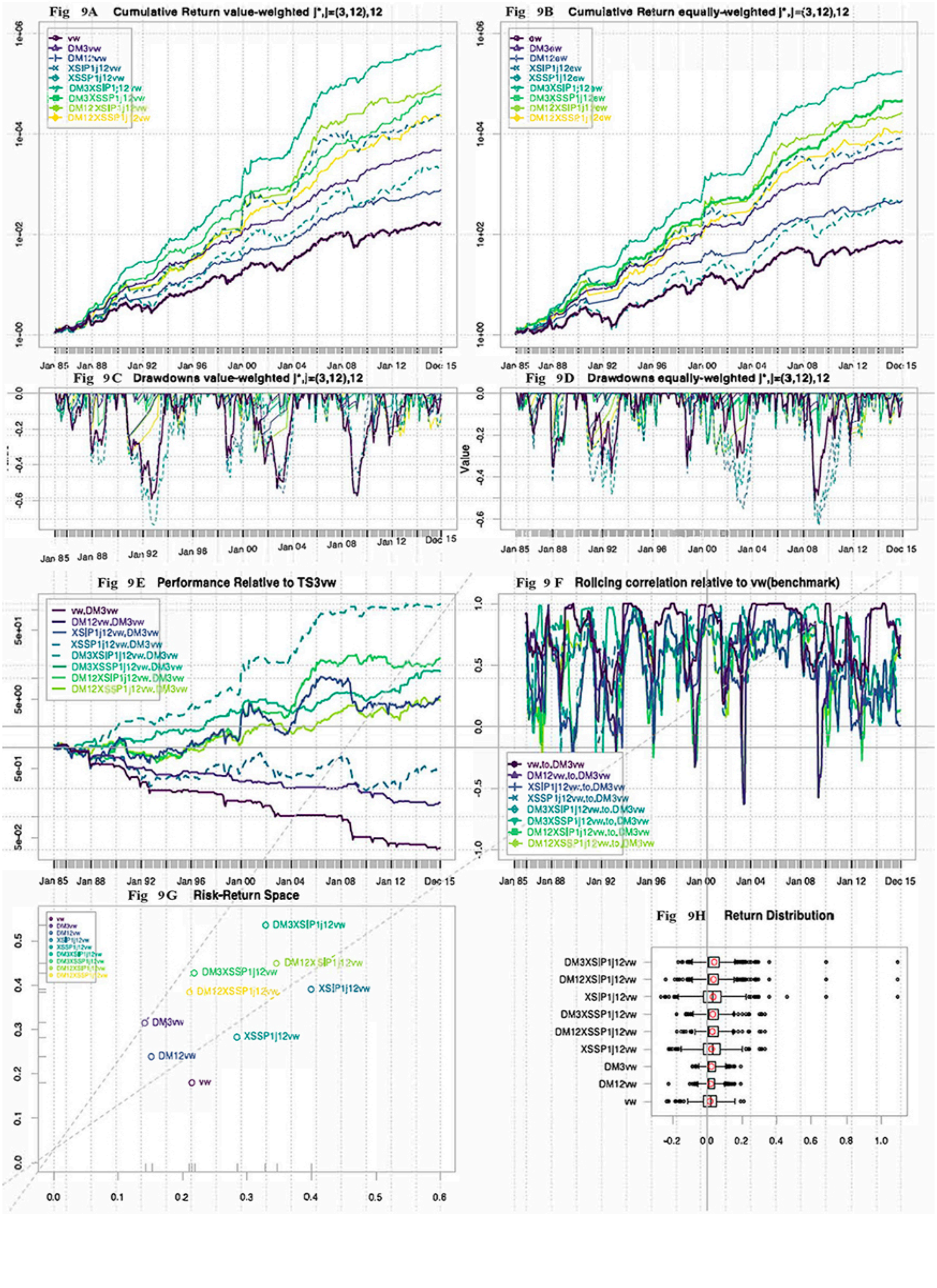


***Table 10: Additional Performance Measures.***

| Relative to benchmark(vW) | DM3vw to vw | DM12vw to vw | XSIP1j12 vw to vw | XSSP1j12 vw to vw | DM3XSIP 1j12vw to vw | DM3XSS P1j12vw to vw | DM12XSIP 1j12vw to vw | DM12XSS P1j12vw to vw |
|---|---|---|---|---|---|---|---|---|
| Alpha | 0.014 | 0.008 | 0.015 | 0.008 | 0.027 | 0.021 | 0.022 | 0.018 |
| Beta | 0.471 | 0.509 | 1.282 | 1.014 | 0.716 | 0.521 | 0.813 | 0.528 |
| Beta+ | 0.753 | 0.656 | 1.697 | 0.825 | 1.426 | 0.767 | 1.364 | 0.64 |
| Beta- | -0.011 | 0.164 | 1.23 | 1.02 | 0.164 | -0.01 | 0.342 | 0.198 |
| R-squared | 0.512 | 0.52 | 0.479 | 0.585 | 0.22 | 0.264 | 0.255 | 0.291 |
| Annualized Alpha | 0.176 | 0.105 | 0.191 | 0.104 | 0.378 | 0.285 | 0.291 | 0.243 |
| Correlation | 0.716 | 0.721 | 0.692 | 0.765 | 0.469 | 0.514 | 0.505 | 0.539 |
| Tracking Error | 0.152 | 0.15 | 0.296 | 0.185 | 0.298 | 0.215 | 0.304 | 0.206 |
| Active Premium | 0.135 | 0.059 | 0.21 | 0.102 | 0.355 | 0.247 | 0.268 | 0.203 |
| Information Ratio | 0.889 | 0.396 | 0.709 | 0.554 | 1.191 | 1.149 | 0.884 | 0.988 |
| Treynor Ratio | 0.499 | 0.322 | 0.238 | 0.201 | 0.618 | 0.654 | 0.443 | 0.567 |
| | DM3vw | DM12vw | XSIP1j12vw | XSSP1j12 vw | DM3XSIP 1j12vw | DM3XSS P1j12vw | DM12XSIP 1j12vw | DM12XSS P1j12vw |
| Observations | 372 | 372 | 372 | 372 | 372 | 372 | 372 | 372 |
| Minimum | -0.0868 | -0.2242 | -0.268 | -0.2234 | -0.1678 | -0.1777 | -0.2407 | -0.1756 |
| Quartile 1 | 0.0025 | 0.0016 | -0.0215 | -0.0213 | 0.0028 | 0.0025 | 0.0019 | 0.0024 |
| Median | 0.0109 | 0.0092 | 0.0289 | 0.0287 | 0.0113 | 0.011 | 0.0107 | 0.0108 |
| Arithmetic Mean | 0.0239 | 0.019 | 0.0335 | 0.0243 | 0.0399 | 0.0319 | 0.0354 | 0.0292 |
| Geometric Mean | 0.0231 | 0.0181 | 0.0278 | 0.0209 | 0.0364 | 0.0301 | 0.0313 | 0.0274 |
| Quartile 3 | 0.0448 | 0.0403 | 0.0776 | 0.0725 | 0.0656 | 0.0623 | 0.0636 | 0.0606 |
| Maximum | 0.1929 | 0.1929 | 1.0929 | 0.3325 | 1.0929 | 0.3325 | 1.0929 | 0.3325 |
| SE Mean | 0.0021 | 0.0023 | 0.006 | 0.0043 | 0.0049 | 0.0033 | 0.0052 | 0.0032 |
| LCL Mean (0.95) | 0.0197 | 0.0145 | 0.0217 | 0.0159 | 0.0302 | 0.0255 | 0.0252 | 0.0229 |
| UCL Mean (0.95) | 0.0281 | 0.0235 | 0.0453 | 0.0327 | 0.0496 | 0.0384 | 0.0456 | 0.0354 |
| Variance | 0.0017 | 0.0019 | 0.0133 | 0.0068 | 0.0091 | 0.004 | 0.0101 | 0.0037 |
| Stdev | 0.0411 | 0.044 | 0.1154 | 0.0825 | 0.0952 | 0.0633 | 0.1003 | 0.061 |
| Skewness | 0.7578 | 0.1597 | 2.6775 | 0.0099 | 4.86 | 1.1856 | 4.1501 | 1.0164 |
| Kurtosis | 1.179 | 3.196 | 21.1796 | 1.5065 | 44.8703 | 4.1765 | 36.9996 | 4.1285 |

# 6. Discussion

A vast body of research has confirmed the persistence and prevalence of cross-sectional price momentum in most developed stock markets around the globe. Even some of the strongest proponents of the EMH, Fama & French (2006) states in “dissecting anomalies”, that the momentum effect is "pervasive". The cross-sectional momentum effect also has proven pervasive in the Norwegian stock market. However, only sparse evidence for a more practically feasible long-only cross-sectional momentum stock strategy have been documented over longer sample periods and even less so for the existence of profitable cross-sectional sector momentum strategies at the Oslo Stock Exchange.

We have seen that cross-sectional price momentum on individual stocks exhibit significant systematic abnormal returns. However this momentum effect is only prevalent in the extreme end of the spectrum (10% decile) for the individual stock strategies. However Cross-sectional sector momentum is not as concentrated and have more significant but less extreme abnormal returns. This findings suggest individual stock momentum to be a more selective method with less noise. It also suggest some connection between sector and individual cross-sectional momentum. I also document that cross-sectional individual stock and sectors exhibit different response to the input parameter, i.e., look-back period. Sector momentum responds relatively more to the short j = 3 and long j = 16 –month look-back period while individual stock strategies responds relatively more to look-back periods from 6-12 months. This finding is consistent with prior studies speculating that the momentum effect is caused by both a behavioral grounded overreaction *and* under reaction. Interestingly, Heidari (2015) documents that when investor overreaction is low the momentum effect are more due to industries. Although certainly not conclusive, this might be some of the mechanism underlying the relatively stronger response to the shorter and longer look-back period from cross-sectional sector momentum relative to individual stocks. In general we have seen that although the shorter five-year sub-sample periods overall outperform the benchmark, longer timeframes exhibit significantly more persistent abnormal return’s. The implication of this finding is to have patience in executing cross-sectional momentum strategies. In general we have seen the top (and bottom) performing decile systematically exhibiting more volatility. This finding clearly links the momentum effect to momentum and is in line with prior studies[14]

For the time-series overlay, a rather surprising finding was the pronounced effect of a three-month look-back period (j*=3) and the marginal decrease in abnormal returns for longer look-back periods. Other academic studies with similar time-series overlays (e.g., Antonacci (2012), Faber (2011), Faber (2013)), uses a twelve-month look-back period. At this stage this finding on the OSE is on the descriptive side and must be validated in further investigations. The overreaching picture from the time-series suggests that given the significantly lower transaction and maintenance costs, a simple time-series overlay to an otherwise broad market portfolio could be a very cost beneficial strategy in relation to the more costly dual-momentum strategies. We have seen that the time-series momentum overlay indiscriminately lifts the performance of the otherwise passive buy & hold sector portfolios. Given that we have seen time-series momentum to work in downtrending markets, this finding illustrates the general the high correlation in equities, especially during recessions.

In a broader context, the findings in this study all indicate predictive power in historical stock prices. This in itself contradicts the classical (weak form) efficient market hypothesis (EMH), and suggests models such as the adaptive market hypothesis (AMH) to be a more useful frame of reference in explaining the nuances of dynamic markets and specifically momentum trading. In this context, the AMH states that only the market participants that are able to adapt will survive and consequently be profitable. Most relevant in the context of this study, are the institutional and behavioral factors affecting adaptation. Accordingly, as the momentum strategies in this investigation evidently have demonstrated the ability to systematically deliver abnormal risk adjusted returns, they should under this theoretical perspective, have inherent properties consistent with superior adaptive abilities relative to the aggregate market. On the institutional side, none of the momentum strategies in this investigation are subject to either allocation constraints, collateral, risk limits or other policies. On the behavioral side, the momentum strategies depends on mechanical trading

[14] I Refer to Antonacci 2014 for a discussion on this point)

rules. This lack of discretionary trading decisions helps mitigate behavioral biases, especially in times of market distress —where research repeatedly show that market participants collectively tend to make choices on less rational grounds. In addition to the discussed behavioral biases implicated in cross-sectional momentum, one can argue that the rules-based time-series momentum strategies also are able to exploit, rather than be adversely affected by some of the most common behavioral biases, e.g., home (equity) bias - difficulty in changing to more attractive markets or loss aversion - the tendency to have stronger behavioral reactions when facing losses(A).

As equity markets are highly competitive and arguably, (for the most part) efficient, one can reason that the momentum strategies´ fundamental source of competitive edge rests on their adaptive abilities relative to the aggregate of market participants. From the mid 1930s up until the mid 2000s, investors with a 10 - 20 year horizon, could expect very similar risk-adjusted returns almost anywhere on the time-curve during this period. Despite frequent business cycles, we have witnessed an almost linear log-cumulative-trend growth curve during this timeframe. In such market environments the traditional investment paradigm under the EMH, CAPM and modern portfolio theory — proposing the use of passively managed low cost index funds and the addition of fixed income to reduce portfolio volatility and drawdowns, have proven quite reasonable. However, the thirty-year bull market in bonds have finally come to an end and investors are now scrambling for safety and return on their capital. Lo (2012) argues that even though investors of different generations have a tendency to view their current environment as something very special and certainly "new", we are genuinely facing a new world order in the markets, at least in relation to the preceding period. Now, quite suddenly after the financial crisis, separating the trend from the business cycle no longer is "business as usual" - as now also the trend component suddenly appear rather stochastic (Refs). Lo (2012, p.4) writes:

> *"the more pressing issue at hand is whether the most recent decade can be ignored as a temporary anomaly……..or if it is a harbinger of a new world order. There is mounting evidence that supports the latter conclusion"*

In this I close with the notion that if we really are facing a new playing field, time-series momentum (trend following) alone or in combination with cross-sectional momentum might be more in tune with the ongoing market realities . If, on the other hand the present economic and financial landscape is a temporary anomaly, the discussed momentum strategies nevertheless have proven an impressive track record, not showing signs of disappearing anytime soon.

## 6.1 Limitations and Future Research

Although the constructed momentum strategies have demonstrated a robust performance, the related transaction costs have not been accounted for. Especially for the more trading-intensive strategies, e.g., dual momentum, transaction costs can over the long term significantly reduce trading profitability. Thus, one endeavor with potentially high practical value would be an analysis with a realistic implementation of all related trading costs, perhaps also including taxes. On another note, the market factor (vw) was constructed from the data material used in this research, however the SMB, HML, PR1YR and LIQ, was as explained in chapter 3 acquired from an external source.  Even though the stock filtering process in this research was inspired by and thus quite similar to the author of the market risk factors, some differences certainly exists. This could potentially have created spurious relationships in the regression analysis.

Related to the momentum strategies, the findings in this research document a relatively weak performance of the losing sectors over the prior intermediate term. Thus, also investigating the short-side of cross-sectional sector momentum strategies could prove worthwhile. In addition, as seen in e.g., Moskowitz and Grinblat (1999), a through analysis of the relationship between sector/industry and individual stock momentum at the OSE could be an interesting undertaking. Another potential venue related to cross-sectional momentum strategies would be to study long(short) positions in an incremental number of single stock positions, and/or to a greater extent examine the particular stocks/companies mainly being responsible for the cross-sectional momentum effect at the OSE. Such an undertaking could potentially increase our understanding related to the momentum phenomena while also opening up to new insights and questions surrounding this particular market in general.

Another limitation found in this and most empirical investigations published on momentum thus far, has to do with the rather naive ranking mechanism between stocks (assets) in the cross-section. In the cross-sectional momentum strategies in this thesis, I have compared the rate of change (ROC) over some given prior timeframe, variants of which are very common. This implies that no care have been taken to adjust for large price movements unrelated to the intended momentum effect, e.g., a takeover or some other non-relevant event. Related, the ranking mechanism does not account for the *normal* volatility of the stocks. Again, we might end up with a number of arbitrary stocks in our portfolio, mistaking a momentum for what in reality is just regular price variations. For future studies I would therefore encourage the construction of more sophisticated ranking mechanisms that to a greater extent enable us improve the ratio of the signal(momentum) to noise (non-relevant volatility). I suspect this will give us additional insight into the anomaly and its causes, while also reducing some of the additional variation associated with cross-sectional price momentum.

Each momentum portfolio presented in chapter 5 are weighted on a value-weighted basis. This method of position sizing cause a random risk bias towards the stock(s) with the greatest market capitalization at that particular point. Similarly, for the equally-weighted portfolios we end up with a random risk bias towards the high volatility stock(s). I therefore encourage the implementation of risk parity sizing to mitigate the probability of being moved by just a few positions. Turning to the subject of time-series momentum, the research presented in this thesis are quite descriptive and barely scratch the surface of the range of possibilities within this exciting, and as it turns out, significantly less researched phenomena. I have presented a time-series (trend following) filter based on the market portfolio(vw "index") that is designed to identify market regime changes in aggregate stocks. In general, I encourage further research on this subject and as a starter, it would be interesting to validate the findings in this research and to a greater extent investigate and explain its rational basis. Investigating time-series on individual stocks themselves under a range of different parameters is yet another potentially intriguing area of research.

# 7. Conclusion

In the empirical investigations presented in this research, I have studied a series of momentum strategies with a practical focus in mind. Specifically, I have investigated a set of long-only cross-sectional stock momentum strategies (research question 1), long only cross-sectional sector momentum strategies (research question 2) and the wide application of a time series overlay either applied to passive buy and hold strategies, sector portfolios (research question 3) or cross-sectional price momentum strategies (research question 4). With respect to the two first research questions, the results presented suggests that both cross-sectional momentum based on long-only individual stocks and cross-sectional momentum strategies based on sectors are able to deliver significant, persistent and robust abnormal returns. For the former, we have seen that the 10 % of stocks with the best performance over the preceding 6-12 months in general tend to exhibit a relative over-performance in the coming month (monthly rebalancing). This is also the case for the cross-sectional sector strategies, albeit to a greater extent the shorter 3 month and to a lesser extent the longer 12 month look-back period.

With respect to the main research question, I have studied the performance of different strategies based on a simple time series overlay (or in other words a trend following filter). First, the findings related to the addition of a time-series overlay to an otherwise passively managed value-weighted market portfolio, suggests that trend following at the OSE have been able to deliver a substantial and significant over-performance relative to the value-weighted market portfolio. In other words, during 1985 to 2015 and different sub-samples within this time-frame, betting on the continuing serial-correlation of the (aggregate) returns at the OSE, have persistently been a profitable strategy. The same robust over-performance have also been documented with the application of a time-series overlay to an otherwise passive buy and hold sector portfolio(s). Related to the combination of time-series and cross-sectional momentum (research question 4), the findings suggest that the this combination potentially can offer both higher returns that we often observe related to cross-sectional momentum, while also capturing the higher returns and substantial risk reduction associated with time-series momentum. The findings related to cross-sectional momentum contribute additional empirical evidence and refinements to the existing literature on the momentum effect at the Oslo Stock Exchange. However, the primary inroads from this study are perhaps the findings related to the implementation of time-series momentum, either as an overlay to a naive buy and hold position or to individual stocks or sector strategies. Although the operationalization of the time-series momentum in this investigation uses a rather rudimentary strategy, it´s simplicity have demonstrated some intriguing attributes in line with other preliminary studies (e.g., Antonacci 2013). At the very least, it is nevertheless exploring new grounds at the OSE and, at least judging by the preliminary findings in this investigation, more effective and just as prevalent and persistent as cross-sectional momentum.

# References:

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## Data Source:

Gics:

https://www.msci.com/gics

## APPENDIX A

***A 1: Stocks missing not due to filtering constraints***

| |
|---|
| GREGOIRE |
| HAFSLUNDB |
| HANDS |
| HENNSMAURITZ |
| INTEROILEXPPRDN |
| JINHUISHIPTRSP |
| MYCRON |
| NOBELBIOCARE |
| NORTRANSOFFSHORE |
| NYCOMEDA |
| NYCOMEDAMERSHAMPLCA |
| NYCOMEDAMERSHAMPLCB |
| NYCOMEDB |
| ODFJELLA |
| ODFJELLB |
| ORKLAB |
| OSLOHAVNELAGER |
| P4RADIOHELENORGE |
| PEPPESPIZZA |
| RESERVOIREXPTECHB |
| RGIANTILLES |
| RIEBERSON |
| RIEBERSONB |