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Mispricing at the Oslo Stock Exchange

How Suitable are the Mispricing Models of Stambaugh and Yuan for Describing Norwegian Stock Returns?

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Abstract

This thesis assesses the suitability of the three- and four-factor mispricing models of Stambaugh and Yuan (2017) in describing Norwegian stock returns in the period between 1998 and 2018. As such, it is one of the first studies of their mispricing factors applied to other capital markets. Using a new data set I find that all of the mispricing factors are found to have a significant effect in describing cross-sectional return differences. In constructing single- and double-sorted test assets on a wide range of anomalies, I observe a strong momentum effect but little evidence of a size and liquidity effect at the Oslo Stock Exchange, inconsistent with some of the earlier evidence from the Norwegian market. When testing the mispricing models against the three-factor models of Fama and French (1993) and Næs, Skjeltorp, and Ødegaard (2009), I find that none of the asset pricing models consistently outperform the others in neither absolute nor relative terms, and that the results of the asset pricing tests are sensitive to both the choice of test assets and weighting schemes. In spanning regressions, neither the three-factor model of Fama and French (1993) nor the three-factor model of Næs et al. (2009) are able to accommodate any the mispricing factors.

Keywords: Asset Pricing; Factor Models; Norway; Anomalies; Mispricing; Stambaugh; Yuan; Momentum.

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This master thesis is written as part of the Master of Science program at the Norwegian School of Economics and constitutes 30 ECTS of the study.

The process of writing the thesis has certainly proved challenging and demanding, but I feel fortunate to be able to study a topic of my own choice. Asset management is becoming increasingly systematic in nature. In the period after the 2008 financial crisis, we have found ourselves in a low return and high regulation world. Meeting liabilities or savings targets with traditional bond investments have become tougher, riskier assets are being more heavily punished by the regulators and also exceed the risk bearing capacity of private investors. This is leading to greater adoption of cross-asset risk premia strategies as an alternative to traditional asset allocation. Thus, examining and challenging factor-based investment models is not only interesting is not only exciting from a personal perspective, but it is also important from a public perspective.

I would like to thank my supervisor, Associate Professor Tommy Stamland, for giving me advice on the choice of a feasible topic, in addition to valuable input and feedback on my work.

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Introduction

Over the course of the past 45 years, since Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973), among others, found that the Capital Asset Pricing Model (CAPM) beta was a positive and significant factor in explaining the cross-section of expected stock returns, hundreds of papers on market inefficiencies which seemingly contradicts the efficient market hypothesis (anomalies) have been written trying to explain cross-sectional differences in return, giving rise to a plethora of proposed factor models (Harvey, Liu, & Zhu, 2016).

The perhaps most famous of these models is the three-factor model of Fama and French (1993) (FF-3), which has taken up a position as a benchmark on which financial economists assess the explanatory power of newly discovered anomalies. Even though an ever increasing number of studies have identified anomalies which neither the CAPM nor the three-factor model can accommodate, few anomalies have been able to sustain a challenge as additional factors[1] (i.e., adding incremental explanatory power). Indeed, even the market and Fama and French (1993) factors have been cast aspersions on, where, for instance, the size effect have been found to vanish during some time periods (Horowitz, Loughran, & Savin, 2000) and the book-to-market effect has been attributed to seasonality (the January effect) and exceptionally low returns on small, young, growth stocks (Loughran, 1997). Moreover, researchers have observed that many of these factors i) struggle to work outside the sample period and the results are hard to replicate (Hou, Xue, & Lu, 2018); ii) are found insignificant when applied to different countries or test-assets (Lewellen, Nagel, & Shanken, 2010; Fama & French, 2012); and iii) even if observed to have predictive power in the past, might fail to predict returns in the future (McLean & Pontiff, 2016). Not only are the existence of these market anomalies disputed among researchers, but whether the sources of their abnormal returns reflect rational or irrational expectations is also a point of controversy. While some scholars argue that in an efficient capital market any characteristic able to predict future returns must represent an underlying risk factor (Fama, 1970), others argue that market frictions which limits arbitrage give rise to sentiment induced mispricing (Lakonishok, Shleifer, & Vishny, 1994; Shleifer & Vishny, 1997).

Although factor models cannot easily distinguish risk from mispricing, they can still be useful in that they can capture both systematic risk factors and/or common sources of mispricing (Hirshleifer & Jiang, 2010; Kozak, Nagel, & Santosh, 2018). At the same

[1]A few notable exceptions include, among others, the momentum anomaly of Jegadeesh and Titman (1993), which motivated the momentum factor of Carhart (1997), and different configurations of investment and profitability factors (see, e.g., Fama and French, 2015; Hou, Xue, and Zhang, 2015).

time, as argued by Stambaugh and Yuan (2017), the proliferation of anomalies is making the need for an alternative factor model, which can accommodate a larger set of market inefficiencies, increasingly clear. Following this line of reasoning, Stambaugh and Yuan (2017) propose two different but similar mispricing factor models, which include factors that average a stock's rankings across multiple anomalies. The authors aim is to achieve a less noisy measure of a stock's mispricing (thus more precisely discern which stocks to go short and which stocks to go long), in other words, the authors argue that anomalies in part reflect mispricing and that mispricing has common components across stocks. The (simple) three-factor mispricing model (M-3) is constructed through combining a market and size factor with a composite mispricing factor, whereas the four-factor mispricing model (M-4) is constructed by combining a market and size factor with two composite mispricing factors, where the mispricing factors are constructed through grouping together the anomalies exhibiting the greatest similarity into two clusters. The anomalies chosen by Stambaugh and Yuan are a prominent subset of 11 anomalies from the literature which have been linked to mispricing interpretations.[2]

The primary objective of this thesis is to test the applicability of the three- and four-factor mispricing models of Stambaugh and Yuan (2017) for the Norwegian stock market. It is often argued that robust factors should be applicable to a homogenous set of other cases (see, e.g., Hsu, Kalesnik, and Viswanathan, 2015), in other words, the effects should persist across different time periods and, under the assumption of globally integrated capital markets, be statistically significant in any country or region. A useful way to assess the robustness of factor models is thus to test their ability to describe stock returns out of sample and in markets aside from the country of discovery. Although there are many potential countries I could have chosen for this analysis, Norway is interesting for several reasons: i) Norway is a small open economy and as such the Norwegian market place arguably has rather different characteristics than the U.S. market place, ii) to the best of my knowledge, there are at the time of writing no other studies applying the Stambaugh and Yuan models to the Norwegian stock market, iii) as noted by Næs et al. (2009), there are few analyses that specifically study the Oslo Stock Exchange (OSE).

In testing the models applicability I replicate the methodology outlined in the paper of Stambaugh and Yuan (2017), and compare the mispricing models to the three-factor model of Fama and French (1993) as well as the three-factor (liquidity) model of Næs et al. (2009)

[2]Namely, i) net stock issues (Ritter, 1991); ii) composite equity issuance (Daniel & Titman, 2006); iii) accruals (Sloan, 1996); iv) net operating assets (Hirshleifer, Hou, Teoh, & Zhang, 2004); v) asset growth (Cooper, Gulen, & Schill, 2008); vi) investment-to-assets (Titman, Wei, & Xie, 2004); vii) financial distress (Campbell, Hilscher, & Szilagyi, 2008); viii) momentum (Jegadeesh & Titman, 1993); bankrupcty probability (Ohlson, 1980); x) gross profitability premium (Wang & Yu, 2013); and xi) return on assets (Wang & Yu, 2013).

(NSO), who observe that a model consisting of a market-, size-, and liquidity-factor[3] is able to explain returns on the OSE reasonably well. Additionally, I construct a Norwegian three-factor mispricing model (NOR), that combines a market and size factor with a Norwegian composite mispricing factor, which averages the scores of the Stambaugh and Yuan anomalies that survives adjustments to more severe restrictions as well as the liquidity anomaly. One could, of course, argue that a factor constructed on the basis of the most robust in-sample anomalies would be subject to biases arising from data mining. While this may be true, averaging across several variables which do not capture systematic risk or mispricing effects might contaminate the factor with extraneous information (Stambaugh & Yuan, 2017), by subjecting the factor to more severe restrictions I am hoping to capture more robust effects.

As there are few extensive analyses of the Norwegian stock market except for the study of Næs et al. (2009), assessing the presence of the anomalies underlying the models above in the Norwegian market thus follows naturally as a secondary goal of this thesis. The traditional approach in studies of the U.S. stock market, is to sort companies into portfolios using NYSE deciles according to a firm characteristic (for instance, size, book-to-market, etc.) and then running a simple t-test to examine the average returns of the two extreme portfolios. In addition to the traditional approach, where I for the Norwegian case sort companies into portfolios based on OSE quintiles,[4] I also run the monotonic relation test of Patton and Timmermann (2010) to test whether returns are monotonically increasing or decreasing across the portfolios.

This thesis adds to the existing literature in three ways. First, it is one of the first studies of the mispricing factors models of Stambaugh and Yuan (2017) applied to other capital markets, a useful way of ascertaining whether the models can accurately describe assets returns or if they merely detect sample-specific effects. Second, as far as I know, there are at the time of writing no studies assessing the presence (or absence) of such a wide range of anomalies in the Norwegian stock market. Third, I test the asset pricing models on a wide range of different test assets and across both equal- and value-weighted portfolio returns.

All of the mispricing factors analyzed in this study are found to deliver economically and statistically significant returns at least at the 5 percent level. Moreover, their returns survive adjustment to both the CAPM, FF-3 and NSO model in spanning regressions.

[3]Note that Næs et al. (2009) uses the relative bid-ask spread in their study to proxy for liquidity, however, due to difficulty in obtaining data on the bid-ask spread, I use the Abdi and Ranaldo (2017) 2-day corrected bid-ask spread estimator to proxy for liquidity.

[4]Ødegaard (2018) finds that one needs at least 10 Norwegian stock to form a diversified portfolio, sorting the stocks into 10 portfolios (as is customary in the U.S.) would thus lead to an insufficiently low number of stocks per portfolio.

The market factor is also found to be significant at the 10 percent level, but none of the other factors tested are found to be significant. However, when assessing the model fit, the results are more mixed, where none of the asset pricing models consistently outperform the others across a wide range of test assets. For example, both the M-3 and NOR models (and in one case the NSO model) are able to accommodate the richer sets of anomalies in the sub-period between July 2005 and June 2018 using value-weighted test assets, but all models are rejected by the Gibbons, Ross, and Shanken (1989) (GRS)-test when using equal-weighted test assets. And even though the M-4 model has the lowest mean absolute pricing error and explains more of the systematic time-series variation in realized returns, for both equal- and value-weighted sorts, on subsets of anomalies across the full sample period, it is generally rejected at least at the 1 percent level by the GRS-test. Moreover, I find strong evidence for the presence of a momentum effect at the OSE, where portfolios long in past momentum winners and short in past momentum losers delivers a significant alpha when adjusted for both the CAPM, FF-3, M-3, and M-4 models. On the other hand, I find little evidence of a size and liquidity effect, inconsistent with previous results of Næs et al. (2009).

The rest of this thesis is structured as follows. In Section 2 I give an overview of the theoretical framework for factor pricing models, followed by an introduction to the literature on anomalies treated in this paper and an overview of some of the ongoing controversies within factor investing literature. A description of the empirical methods used in this paper is given in Section 3. Section 4 reports how the data set is constructed and sourced. In Section 5 I present the results of the analysis. Finally, in Section 6, I give some concluding remarks and point towards further research possibilities.

Theory and Literature Review

The literature on asset pricing and factor-models is vast and by necessity I have had to restrict my discussion to a subset of articles. In the following, I give a brief introduction to: the theory on factor pricing models;[5] the market-anomalies treated in this paper; as well as recent critique of factor based investing.

2.1 Factor Theory for Pricing of Equities

From the dividend discount model, we know that the present value of a stock market can be expressed as,

$$P_{M,0} = \sum_{i=1}^{n} \sum_{t=0}^{\infty} E_0 \left[\frac{D_{i,\tau}}{(1 + r_{i,\tau})^{\tau}} \right] \tag{1}$$

where $P_{M,\tau}$ is the value of the market M at time τ, with n different companies, i. $E[D_{i,\tau}]$ is the expected cash flow of company i at time τ and $E[r_{i,\tau}]$ is the expected return for a cash flow occurring at time τ (see Næs et al., 2009). Assuming a risk-free rate, r_f, we can define the excess return, or, risk premium as, $R_{i,\tau} = E[r_{i,\tau}] - r_{f,\tau}$. From the present value formula in Equation (1) we see that the market return can be affected by different factors through three channels: future cash flows, the risk premium, the risk-free rate, or a combination of these. Assets earn their risk premiums due to their exposure to underlying risk factors, and factor pricing models try to explain the risk premia observed in the market. Building on previous work by Markowitz (1952), the Capital Asset Pricing Model (CAPM) of Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966) is the first theory of factor risk. Unconditionally, the CAPM can be expressed in expected returns form as,

$$E[r_i] - r_f = \beta_{i,m} \left(E[r_m] - r_f \right) \tag{2}$$

or equivalently, letting $\lambda_m = E[r_m] - r_f$,

$$E\left[R_i\right] = \beta_{i,m} \lambda_m \tag{3}$$

[5]The Section on factor theory is based on Chapters 1–4, 6–8, and 14 of Ang (2014), as well as, Chapters 1 through 9 of Cochrane (2005), to which I refer for more details.

where $\beta_{i,m} = Cov(r_i, r_m)/Var(r_m) = \rho_{i,m}\sigma_i/\sigma_m$ and $\rho_{i,m}$ is the correlation between asset i's return and the market return, σ_i is the standard deviation of the return of asset i and σ_m is the standard deviation of return of the market factor. In other words, beta is a measure of an assets co-movement with the market portfolio. In equilibrium-based models, the marginal investor is assumed to be risk averse. From Equation (2) we can see that a high beta implies a relatively larger contribution to the risk of the portfolio, thereby commanding a higher risk premium (average returns), conversely, low beta assets implies a relatively lower contribution to the risk of the portfolio and risk averse investors need not be compensated to the same extent for holding them, or, as stated by Cochrane (2005, p. 156): "Beta drives average returns because beta measures how much adding a *bit* of the asset to a diversified portfolio increases the volatility *of the portfolio.*" I.e., according to the CAPM, in equilibrium, assets that do poorly in the states when the market is down must reward investors with higher risk premiums.

The CAPM is, although useful, often seen as an empirical failure and there is a vast and ever-increasing literature of return patterns which the CAPM fails to explain. Moreover, it is based on some very simplifying assumptions, one of which is that the investors only live for one period. Consequently, over the years since the first empirical tests of the CAPM, there have been developed two main theoretical approaches to overcome these challenges, the intertemporal CAPM (ICAPM) of Merton (1973) and the arbitrage pricing theory (APT) of Ross (1976). Although I will not go into an extensive discussion on the differences in the theoretical foundations of these models,[6] in empirical work, the main difference between the ICAPM and APT is the inspiration for factors; where the ICAPM focuses on state variables capable of describing the conditional distribution of future returns, the APT focuses on statistical analysis of co-movement of returns. In an unconditional framework, both the APT and ICAPM can be expressed in multiple-beta form as,

$$E[R_i] = \sum_k \beta_{i,k}\lambda_k \tag{4}$$

where $\beta_{i,k}$ is the exposure of asset i to factor k and λ_k is the risk premium of factor k. As can be seen in Equation (4), while the CAPM defines bad states through the market factor as times of market downturns, multifactor models capture multiple definitions of bad states defined by different factors, $\mathbf{f} = (f_1, f_2, \ldots, f_K)$. Like in the CAPM, the factor(s) cannot be diversified away. Hence, assuming equilibrium (no arbitrage), investors need to be compensated for facing risk through multiple factors. Further, observe that in both the CAPM and multifactor models diversification works, hence idiosyncratic risk, i.e. the

[6]The interested reader is referred to Chapter 9 of Cochrane (2005).

portion of an assets volatility not related to the factor(s), does not command a premium. Thus, for both the CAPM and multifactor models, the risk premium of an asset is captured in its betas, where assets paying of in bad states are attractive and assets paying off in good states command higher risk premiums.

Broadly speaking, investment strategies using factor models can be split into two camps: macro, fundamental models (economic growth, inflation, productivity, etc.) and investment-style (the CAPM, value, size, etc.), but in principle one can utilize every distilled signal (anomaly) to drive or protect ones portfolio.

2.2 The Anomalies

As previously noted, over the past decades researchers have identified numerous patterns in average stock returns which cannot be explained by the CAPM. This section gives a brief introduction to some of the articles relating to the anomalies discussed in this paper.

The first anomaly whose presence was noted is the so-called **beta-anomaly**. One of the first tests of the CAPM was the seminal study of Black et al. (1972), which, along with Haugen and Heins (1975), found that the security market line is flatter than predicted by the CAPM, implying that high beta stocks do not produce substantially higher returns than low beta stocks. Consequently, as noted by Black (1993), on a risk-adjusted basis, a portfolio that is long low beta stocks and short high beta stocks should produce a positive and significant alpha. Although contested,[7] the beta-anomaly has been demonstrated to exist in a number of equity markets around the globe and across different asset classes, such as bonds, currencies, and commodities (Blitz and Vliet (2007), Frazzini and Pedersen (2014)), and has been contributed to both leverage constraints and behavioral biases (Frazzini and Pedersen (2014); Barberis and Xiong (2012)). A related phenomenon is the **idiosyncratic volatility puzzle**. Ang, Hodrick, Xing, and Zhang (2006) documents a negative relation between idiosyncratic volatility (IVOL), measured relative to the Fama and French (1993) three-factor model, and subsequent stock returns. The IVOL-anomaly is puzzling in the sense that according to traditional asset pricing theories there should either be no relation (assuming complete and frictionless markets with investors holding well-diversified portfolios), or a positive relation (assuming incomplete markets with frictions and investors holding poorly-diversified portfolios).[8] Many studies have been written

[7] Using different data, Easley, Hvidkjaer, and O'Hara (2002) find a negative relation, Fama and French (1992, 1993) found no significant relationship after controlling for the size effect, whereas Kothari, Shanken, and Sloan (1995) and Jaganathan and Wang (1996) find a positive relation (although the latter uses a conditional version of the CAPM).

[8] See, for example, Merton (1987); Hirshleifer (1988).

trying to explain this effect, among others the papers of Stambaugh, Yu, and Yuan (2015), Stambaugh and Yuan (2017), who contributing it to arbitrage asymmetry, arbitrage risk, and mispricing.

Another prominent anomaly is the **size effect**, documented by Banz (1981) and Reinganum (1981), who found that stocks with low market capitalization tend to outperform stocks with large market capitalization. The size-effect have been demonstrated European markets by, among others, Heston, Rouwenhorst, and Wessels (1995) and in the Norwegian market by Heston et al. (1995) and Næs et al. (2009). Even though the size effect is one of the most well-documented anomalies (Dimson & Marsh, 1999), it has been known to vanish during time periods.[9] The size effect is often attributed to the riskier nature of small firm versus big firms (see, e.g., K. C. Chan, Chen, and Hsieh (1985), N.-f. Chen (1981, 1982)).

One of the most robust asset pricing anomalies is the **momentum effect** discovered by Jegadeesh and Titman (1993), who documented that buying recent past high return stocks and selling recent past low return stocks generates risk-adjusted alpha. The momentum effect is also one of the most researched anomalies outside the U.S, and has been observed in numerous equity markets by, among others Rouwenhorst (1998), K. Chan, Hameed, and Wilson (2000), Heston, Rouwenhorst, and Wessels (2003), and Artmann et al. (2012). In Norway, Nygaard (2011) finds a momentum effect in small caps, which he ties to household investor trading patterns and the disposition effect,[10] thereby linking it to prospect theory (Kahneman & Tversky, 1979). Næs et al. (2009), however, finds only weak evidence to support the momentum effect for stocks at OSE.

Value strategies can be traced back to Graham and Dodd (1934) and have been documented in numerous papers.[11] Stattman (1980) and Rosenberg, K., and Lanstein (1985) observe that stocks which have high book values relative to their market values ("value stocks") systematically outperform stocks which have low book values relative to their market values ("growth stocks"), this is known as the **value-effect** or in this case the book-to-market (BM) effect, and have later been demonstrated by both Lakonishok et al. (1994) and Fama and French (1992), among others. Along with the size effect, the value effect is often interpreted as compensation for the risk of financial distress.[12] Globally, the value

[9] See, e.g., Horowitz et al. (2000) who find no size effect between 1982–1997 for the U.S. and Artmann, Finter, Kempf, Koch, and Theissen (2012) who finds no evidence for the size effect in German markets (as opposed to Heston et al. (1995)).

[10] See also, Grinblatt and Han (2005) and Shefrin and Statman (1985).

[11] One of the first to document that companies with value characteristics have superior performance was Basu (1977, 1983). Using the price-to-earnings ratio as a proxy for value, he finds value strategies to produce both an absolute and risk-adjusted alpha in the U.S. market.

[12] To see this, consider the dividend discount model in Equation (1), where companies with relative low

premium has been both extensively demonstrated and disputed,[13] and Næs et al. (2009) find no evidence of a value premium for the Norwegian market. Related to value strategies are strategies based on profitability. Fama and French (2006) observe that profitable firms earn higher subsequent returns than less profitable firms. Novy-Marx (2013), arguing that gross profit is the cleanest measure of true economic profitability, show that a higher gross profit to assets earns higher returns, coining it the **gross profitability premium** (GPP). L. Chen, Novy-Marx, and Hsieh (2010) observe that higher past returns earn higher future returns, measured by the ratio of **return on assets** (ROA). Wang and Yu (2013) investigates both risk-based and mispricing-based explanations, and find that it exists primarily among firms with high arbitrage costs or information uncertainty.

As previously noted, financial distress is often cited as a reason behind differences in expected cross-sectional returns. Ohlson (1980) gave an early contribution to this side of the anomaly literature by estimating the bankruptcy probability of firms through the **O-Score** measure, based on different accounting measures. In a later study, Campbell et al. (2008) use primarily market data in estimating a dynamic logit model of **failure probability** (distress). Both studies find that firms with a higher probability of failure earns abnormally lower subsequent returns. The latter argues that these patterns are more pronounced for stocks with possible informational or arbitrage related frictions, and are inconsistent with the risk-compensation explanation of the size and value effects.

A characteristic that has been proposed to explain both the size, value, and momentum effect is the levels and variation in a company's **liquidity**.[14] A problem with the liquidity is that it has multiple dimensions (how much, how fast, and at which price can an investor trade?), which has led to a wide variety of different liquidity measures with no clear consensus on which one to use (see e.g. Johann and Theissen (2017)). For example, Stoll and Whalley (1983) and Amihud and Mendelson (1986) uses the daily (closing) bid-ask spread; Hasbrouck (2009) uses a Gibbs estimate based on the daily closing prices; Næs et al. (2009) uses the daily relative spread (and finds liquidity a priced factor in the Norwegian market); Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) uses the (daily) illiquidity measure of Amihud (2002); whereas Brennan and Subrahmanyam (1996), Easley et al. (2002), Sadka (2006), Korajczyk and Sadka (2008) uses different high-frequency measures. Nevertheless, the liquidity as an anomaly has been extensively documented in the asset pricing literature. In my work, I have chosen the 2-day adjusted liquidity spread estimator ($\hat{S}_{two-day}$) of Abdi and Ranaldo (2017). The reason for this is threefold: First, even though

(high) book values relative to market values imply high (low) future earnings and/or low (high) risk.

[13]See, for instance, Fama and French (1998), Capaul, Rowley, and F. (1993), Hou, Karolyi, and Kho (2011), and Artmann et al. (2012).

[14]See e.g. Acharya and Pedersen (2005), W. Liu (2006), and Sadka (2006).

testing for liquidity effects using a measure further from the estimator used in Næs et al. (2009) could be interesting in itself, I want to see how the liquidity-factor proposed by Næs et al. (2009) has held up in the twelve years since their sample period ended. Second, Compustat does not provide data for estimating the bid-ask spread directly but do provide daily high, low and close prices, which can be used to compute the $\hat{S}_{two-day}$ estimate.[15] Third, although I have also considered using a measure developed by Corwin and Schultz (2012), $\hat{S}_{two-day}$ is the estimator of choice for obtaining accurate level estimates of the bid-ask spread in the comparative analysis of Johann and Theissen (2017).

Numerous studies have documented a negative relation between different forms of corporate investments and expected returns. First documented by Sloan (1996), the **accruals anomaly** relates to the phenomenon of companies which have higher accruals earn subsequently lower returns. Sloan (1996) suggests that investors fixate on the accruals component of earnings. Although shown to be pervasive in the U.S (Lev and Nissim (2006), Fama and French (2008)), the international evidence on the accrual anomaly is mixed (see, for example, Pincus, Rajgopal, and Venkatachalam, 2007; Leippold and Lohre, 2012). Hirshleifer et al. (2004) find that companies with relatively more **net operating assets** (NOA) earn lower subsequent stock returns than companies with relatively less net operating assets, arguing that investors focus on accounting profitability while ignoring cash profitability. Cooper et al. (2008) observe that **asset growth** is a strong negative predictor of future stock returns, believing the phenomenon to arise from an initial overreaction from investors when judging the prospects of a company after expansion. Titman et al. (2004) and Xing (2008) finds that higher past investment leads to lower future returns, measured by the ratio of **investments-to-assets** (ITA), the former attributing this to an initial underreaction to empire building behavior of managers. Finally, Ritter (1991) and Loughran and Ritter (1995) show that in years following stock issues, companies that issue stock underperform nonissuers. Daniel and Titman (2006); Pontiff and Woodgate (2008); and Fama and French (2008), building on the aforementioned studies along with the paper of Ikenberry, Lakonishok, and Vermelean (1995), observe a negative relation between stock issues and expected returns. Following Stambaugh and Yuan (2017), I analyse both the **composite equity issuance** (CEI) measure of Daniel and Titman (2006) and the **net stock issues** (NSI) measure of Fama and French (2008).

As already alluded to, researchers debate both the consistency and existence of these anomalies, but a perhaps even more controversial topic is whether these anomalies reflect rational or irrational expectations, are the result of data mining, or whether they are possibly time varying and/or market dependant.

[15] See Appendix A for a details.

2.3 Controversies

Empirical tests of asset pricing models, such as those discussed in Section 2.1, which use realized returns to proxy for expected returns, cannot easily distinguish risk and mispricing. Fama (1970) argues that in a rational world with perfect capital markets, any characteristic (or, anomaly) able to predict return must represent a risk factor. In a series of articles Fama and French advocate that the observed return patterns of stocks favour risk-based explanations, arguing that the fluctuations in monthly returns of, for instance, value stocks are fundamentally different from those of growth stocks.[16] This, obviously, implies that investors in value stocks are exposed to different risk factors than investors in growth stocks, for which they require different return premiums.

However, Lakonishok et al. (1994) observe that investors tend to overvalue stocks that have grown in the past, arguing that value strategies deliver abnormal returns not because these strategies are fundamentally riskier, but because of suboptimal behavior of the average investor. LaPorta, Lakonishok, Schleifer, and Vishny (1997) and Skinner and Sloan (2002) also argue that the value effect is due to systematic mispricing, where the latter attributes this to (asymmetric) expectational errors about future earnings performance between value and growth stocks. In perfect capital markets, such mispricing would, of course, be arbitraged away. However, as argued by Shleifer and Vishny (1997), while textbook arbitrage requires no capital (long-short, zero investment portfolios) and entails no risk, in reality there are both risk and capital demands that deter arbitrage.[17] Ali, Hwang, and Trombleya (2003) also observes that the book-to-market effect is higher among stocks with higher idiosyncratic volatility, higher transaction costs, and lower investor sophistication, lending support to mispricing explanations. McKinlay (1995) analyze several different nonrisk based explanations, namely biases introduced into the empirical metodology, market frictions, and irrational behavior. Daniel and Titman (1997) argue that the expected return of a stock seems to be determined more by its characteristics (if it is a value or growth stock) rather than by its return pattern (if it co-moves with value or growth stocks). Understanding where the returns are coming from is key for a number of reasons. As argued by Cochrane (2005), if predictability of average returns reflect rational risk aversion it is more likely to persist, but if it reflects irrational risk aversion it is less likely to persist. Furthermore, a better understanding of the sources of return will allow us to build portfolios

[16]See Fama and French (1992, 1993, 1995, 1996, 1997, 1998).

[17]Some limits to arbitrage frequently mentioned in the literature are: transaction costs; borrowing fees for short-selling; leverage constraints; benchmarking; market and funding liquidity; and risk of slow moving capital (which might even increase the pricing dislocation instead of wiping in out in the short term), exposing money managers to agency issues (job-loss risk) or liquidity risk (margin calls). See, for instance, Black (1972), Baker, Bradley, and Wurgler (2011), Brennan, Cheng, and Li (2012), and Frazzini and Pedersen (2014).

with higher expected return for any given level of risk (Daniel & Titman, 1998).

More recently researchers have pointed out that i) many factors are far from normal in distribution and have time varying correlation with other factors, leading to a loss of payoff transparency (Arnott, Harvey, Kalesnik, & Linnainmaa, 2019; Barroso & Santa-Clara, 2016; Hsu et al., 2015); ii) many of the models struggle to work outside the sample period; the results are hard to replicate and hugely dependent on the weighting scheme (Hou et al., 2018; Plyakha, Uppal, & Vilkov, 2014); and/or iii) even if they had predictive power in the past does not mean they will work in the future—in fact McLean and Pontiff (2016) find that some stock market anomalies are less anomalous after publication, observing that factor premiums were inflated by 26% in out-of-sample tests and that after publication the premium falls by an average of 32%, linking their discussion to both limits to arbitrage and mispricing. Moreover, many of the anomalies are found not to be significant when applied to different countries or test-assets, as pointed out by Lewellen et al. (2010) for the US market and Fama and French (2012) for an international sample, and for smaller markets, Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2017) note that a lack of stock market depth renders many factor strategies unobtainable.

Furthermore, given the number of academic and industry scholars working on this topic, it seems inevitable that all the data mining will result in some positive outliers. Much of the literature on robustness testing of anomalies have focused on techniques in statistical inference and inference in the presence of statistical biases.[18] Lo and MacKinlay (1990) investigate whether tests of asset pricing models may be biased due to data mining, more specifically they describe how portfolio-sorting based on different empirical regularities give rise to biases when running them through empirical tests. Lewellen et al. (2010) also critique the common approach of (only) testing factors against size and book-to-market portfolios, due in part to the strong covariance structure of these portfolios. Shumway (1997) documents a large delisting bias in the Center for Research in Security Prices (CRSP) database. Shumway and Warther (1999) investigates this delisting bias in CRSP's Nasdaq data and finds no evidence of a size effect once the delisting bias is corrected for. Further, they argue that as Banz (1981) finds the size effect to be most prevalent among smaller stocks, and Nasdaq stocks are the smallest in the (U.S.) marketplace, this is strong evidence against the size effect, echoing Lo and MacKinlay (1990) and Black (1993) which argue that the size effect is due to data mining rather than underlying risk-factors. Harvey et al. (2016) argue that due to a limited amount of data (nearly all of the literature uses data from the CRSP database), increase in computational power, and as the low fruit has already been picked (i.e., the rate of discovering a true factor has likely decreased) the t-statistic of 2.0 commonly used as a threshold should be increasing over

[18]See, for example, Leamer (1978);Shanken (1985, 1992).

time.[19] Hou et al. (2018) examines 452 return anomalies and find that, when controlling for microcaps, 65% fail to replicate. By increasing the hurdle on the t-statistic, as proposed by Harvey et al. (2016), the number of insignificant anomalies rises to 380. Moreover, even if the factor is statistically significant, their returns are often much lower than originally reported, consistent with the findings of McLean and Pontiff (2016).

A key question an investor could ask in judging anomaly returns is: what is the economic rationale behind it? In a portfolio context, adding a random factor can improve risk-adjusted performances, but this is not much better than including a sports bet to an investment portfolio.[20] Hsu et al. (2015) propose a more practitioner-friendly three-step heuristic approach for determining the robustness of an anomaly: i) it has to have been debated and validated in numerous papers published in top-tier journals, i.e., the economic foundations must be sound and well documented. ii) it has to be applicable to a homogeneous set of other cases, and iii) survive reasonable adjustments to the construction of the factor.

[19]In a related study, Harvey (2017) also points to the incentive to cheat in the process of producing "significant" results through direct and indirect p-hacking (reselecting sample criteria and test specifications until insignificant results become significant), due to the competition for top-tier journal space.

[20]As Hsu et al. (2015, p.89) points out: "[G]iven the natural cross-sectional variance in returns, a portfolio strategy whose mean excess return is 0 with a tracking error of 4% has roughly a 5% chance of outperforming its benchmark by 1% in a 40-year backtest. Without careful robustness verifications, 1 in 20 portfolio simulations would accidentally look attractive."

Empirical Methodology

This study tests for both the presence of stock market anomalies at the Oslo Stock Exchange and the ability of the mispricing models of Stambaugh and Yuan (2017) to accommodate them. In assessing the applicability of the Stambaugh and Yuan models, I compare their results to that of the three-factor model of Fama and French (1993), the three-factor model of Næs et al. (2009), and a three-factor composite mispricing model based on the models of Stambaugh and Yuan (2017) adapted to the Norwegian market.

In Sections 3.1 and 3.2 below, I detail how the model components are constructed, i.e., the testing and factor portfolios. The portfolios are constructed by sorting on various characteristics discussed in the papers of Fama and French (1993), Næs et al. (2009), and Stambaugh and Yuan (2017), namely: size; book-to-market (BM); liquidity; idiosyncratic volatility (IVOL); net stock issues (NSI); accruals; composite equity issuance (CEI); investments-to-assets (ITA); net operating assets (NOA); distress; O-score; momentum; return on assets (ROA); asset growth; gross profitability premium (GPP); as well as beta. The construction of these anomalies are detailed in Appendix A, along with their summary statistics and correlations in Appendices C and F, respectively. In Section 3.3, I describe the empirical framework used for testing the factor models.

3.1 Test Assets

As is common in the literature I group stocks into portfolios, thereby decreasing pricing variations arising from firm specific effects and reducing the pricing problem to analyze the effects of systematic risk factors.

3.1.1 One- and Two-Dimensional Portfolio Sorts

Although it is customary in U.S. studies to split single-sorted portfolios into deciles (and conduct a 5 x 5 sorting scheme for the double-sorted portfolios), doing so with the limited number of Norwegian stocks would lead to an inadequately low number of stocks per portfolio.[21] Thus, for the one-dimensional sorts, I group the stocks into 5 portfolios based on the quintile breakpoints. I then calculate both equal- and value-weighted returns,[22]

[21] Ødegaard (2018) finds that one needs at least 10 Norwegian stocks to form a diversified portfolio.

[22] The value-weighted portfolio returns in month t is calculated as,

$$r_{PF,t} = \sum_{i=1}^{n} \frac{r_{i,t} \times ME_{i,t}}{ME_{PF,t}}$$

resulting in two sets of 5 portfolios. The portfolios are sorted such that a high score on the respective characteristic is associated with low future return in the literature. For example, a stock with the high (low) past momentum gets assigned to the low (high) quintile, whereas a stock with a high (low) market equity gets assigned to a high (low) quintile.[23]

It is important to note that equal and value-weighted portfolios offer different portfolio dynamics. Specifically, an equal-weighted portfolio should have a tendency for higher turnover, due to its (much) more frequent rebalancing and have a slight positive value bias due to its embedded "buy low, sell high" property, where readjusting the portfolio back to equal weights (as opposed to letting them flow) involves consistently selling winners and buying losers.

I also form different two-dimensional portfolios by independently sorting the stocks based on their values on two different characteristics. Doing so enables us to analyze the interrelations between the respective characteristics. To create a sufficient number of observations in each portfolio I categorize the stocks into 9 (3 x 3) portfolios based on tertile breakpoints, before calculating equal- and value-weighted monthly returns on the resulting portfolios.

3.1.2 Industry Portfolios

Following the recommendation by Lewellen et al. (2010), who critize the practise of using only double sorted portfolios on size and book-to-market, I also report the results from using industry portfolios (as well as various double sorted portfolios) in Appendix I.

Using the Global Industry Classification Standard (GICS), developed by Morgan Stanley Capital International (MSCI) and Standard & Poors (S&P), I group the stocks into 11 portfolios based on the GICS code provided by Compustat Global: Energy (GICS = 10); Materials (GICS = 15); Industrials (GICS = 20); Consumer Discretionary (GICS = 25); Consumer Staples (GICS = 30); Health Care (GICS = 35); Financials (GICS = 40); Information Technology (GICS = 45); Communication Services (GICS = 50); Utilities (GICS = 55); and Real Estate (GICS = 60). I then calculate both equally and value-weighted returns, resulting in two sets of 11 portfolios.

I report the summary statistics of the industry portfolios in Appendix D.

where $n \in \{1, \ldots, N\}$ is the number of stocks in the portfolio, $r_{i,t}$ is the return on stock i in month t, $ME_{i,t}$ is the market capitalization of company i at the end of month t, and $ME_{PF,t}$ is the aggregate market capitalization of all n stocks in the portfolio at the end of month t.

[23] Note that this, of course, has no impact on the results and the only reason for doing so is to save time in the computation of the mispricing measures and MR-tests (discussed further down).

3.2 Factor Portfolios

The first factor is the (excess) value-weighted market return, $RMRF = r_m - r_f$ which is standard in the literature. However, due to OSE being dominated by a few large companies, the value-weighted portfolio will to a large extent be dominated by those companies(Næs et al., 2009). Consequently, similar to Næs et al. (2009) I also construct an equal-weighted market factor, $RMRF_{EW}$, which I also use to assess the model fit.

3.2.1 The Fama-French and NSO-Factors

The Fama-French factors are constructed using the 6 value-weighted portfolios formed on size and book-to-market, the construction of which is detailed in A. As opposed to the other factors (and test assets) studied in this paper which are updated monthly, the Fama-French factors are updated annually, however the returns are observed at the monthly frequency like all the other factors. Following the methodology of Fama and French (1993), SMB is constructed as the return difference between a portfolio of small stocks and a portfolio of big stocks, constructed to be neutral with respect to book-to-market. Likewise, HML is the return difference between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks, constructed to be neutral with respect to size. Specifically, at the end of June of each year, I use independent 2 x 3 sorts to allocate all the stocks in the sample into two size groups and three book-to-market groups. The two size groups are split along the OSE median, where big stocks are above the median market equity and small stocks below. The book-to-market groups are split at the 30th and 70th OSE percentiles, where high book-to-market stocks are in the top 30 percent, neutral book-to-market stocks are in the middle 40 percent, and low book-to-market stocks are below the 30th percentile. SMB is then formed as the difference between equal-weighted averages of the returns on the three small stock portfolios and the three big stock portfolios, $SMB = 1/3(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - 1/3(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$. Similarly, HML is the difference between equal-weighted averages of the returns on the two high book-to-market (value) stock portfolios and the two low book-to-market (growth) stock portfolios, $HML = 1/2(\text{Small Value} + \text{Big Value}) - 1/2(\text{Small Growth} + \text{Big Growth})$.

In forming the LIQ factor, Næs et al. (2009) sorts stocks into three portfolios based on the previous months average relative bid-ask spread. The value of the LIQ factor in month t is then calculated as the difference between the return of the least liquid portfolio and the most liquid portfolio. As Compustat does not provide a measure for the bid-ask spread, I have decided to proxy liquidity by the Abdi and Ranaldo (2017) 2-day adjusted monthly liquidity spread estimator. Although different from the relative spread, it could be argued that the factor should survive reasonable adjustments in regards to its construction (see Hsu et al., 2015). Thus, the *LIQ* factor in this study is constructed as the value-weighted return difference between the return of the least liquid portfolio and the most liquid portfolio, when sorting stocks into three portfolios based on the previous months 2-day adjusted, monthly liquidity spread estimator.

3.2.2 The Mispricing Factors and SMB_M

In constructing the Mispricing Factor model of Stambaugh and Yuan (2017), I consider the same 11 anomalies used in that study, namely: net stock issues; composite equity issuance; accruals; net operating assets; asset growth; investments-to-assets; distress; O-score; momentum; gross profitability premium; and return on assets, henceforth referred to as the Stambaugh and Yuan anomalies. Following the methodology outlined in that paper, constructing the mispricing and size factors for the M-4 model involves averaging various stocks' ranking with respect to the different anomalies. As pointed out by the authors, averaging across several distilled signals as opposed to on a single variable, which is the common approach in the literature, can have both an upside and a downside. Assuming the single variable uniquely captures the systematic risk or mispricing effects, averaging across several variables might contaminate the factor with extraneous information. However, assuming no single variable uniquely captures the underlying information, an averaging across several variables can work better.

Although Stambaugh and Yuan use both a time-series and cross-sectional approach to construct the mispricing clusters, I have chosen to use only a time-series approach in an effort to limit the scope of the study. The first step of the clustering procedure is to, for each anomaly i, compute the spread, $R_{i,t}$, between the value-weighted returns in month t on the stocks in the first and fifth OSE quintile of the ranking variable in a sort at the end of month $t-1$, where the ordering process produces a positive alpha in the regression,[24]

$$R_{i,t} = \alpha_i + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \varepsilon_{i,t} \tag{5}$$

where $RMRF_t$ and SMB_t are the market and size factors of Fama and French (1993) discussed in Section 3.2.1. The second step is to compute the correlation matrix of the estimated residuals in equation (5). Similarly to the study of Stambaugh and Yuan, the data for the ROA and distress anomalies only starts in October 2004 and July 2005, respectively, whereas the rest of the sample runs from July 1998 through June 2018. To

[24]The results of this regression for the case of both equal- and value-weighted returns are summarized in Appendix E

deal with the heterogeneous starting dates, the correlation matrix is estimated using the maximum likelihood estimator of Stambaugh (1997). The final step is to convert the correlation matrix to a distance measure analyzed by Ahn, Conrad, and Dittmar (2009), and forming two clusters by using the clustering method of Ward (1963).

The first cluster, giving rise to what Stambaugh and Yuan call the management related factor ($MGMT$), contains composite equity issuance; accruals; net operating assets; asset growth; gross profitability premium; and investments-to-assets, whereas the second cluster, which forms the basis of the performance-related factor ($PERF$), contains distress; O-score; momentum; return on assets; and net stock issues. The keen reader will have noticed that two of the anomalies, namely gross profitability and net stock issues, have traded places relative to the clusters produced in Stambaugh and Yuan (2017). However, when running the same procedure using equally weighted return portfolios, gross profitability ends up in the second cluster, a result which is closer to that of Stambaugh and Yuan. Although analyzing why this is the case is beyond the scope of this study, I note that both net stock issues and gross profitability could be both management and performance related (see, e.g., Daniel and Titman, 2006; Cooper et al., 2008; Greenwood and Hanson, 2012).

The final step in constructing the mispricing measures is averaging each stock's rankings with respect to the available anomaly measures within the two clusters, thereby assigning it two composite mispricing measures, $P1$ and $P2$. Again, following Stambaugh and Yuan (2017), in computing $P1$ and $P2$ I equally weight each stock's ranking across the anomalies.

When constructing the mispricing factors, I require that a stock have non-missing data for at least three of the anomalies in each cluster to be included in the respective factors cluster. Furthermore, for an anomaly to be included in its mispricing cluster I require that at least 30 stocks have non-missing values for that anomaly. The mispricing factors are constructed by applying a 2 x 3 sorting scheme. Each month I sort stock by size an split them into two groups using the median as a breakpoint. Independently, I sort all stocks by $P1$ and assign them to three groups using the 20th and 80th percentiles as breakpoints. A similar sorting procedure is done for size and $P2$. The $MGMT$ factor is constructed by computing the value-weighted returns on each of the four portfolios formed by the intersection of the two size categories with the top and bottom categories for $P1$. The value of the $MGMT$ factor for a given month is then calculated as the simple average of the returns on the two low-$P1$ portfolios less the simple average of the returns on the two high-$P1$ portfolios (see Figure 3.1 below), i.e., a portfolio long in underpriced stocks and short in overpriced stocks. The $PERF$ factor is constructed in the same manner, specifically, long the two low-$P2$ portfolios and short the two high-$P2$ portfolios.

Finally, the SMB factor of Stambaugh and Yuan (2017) is computed in a different way

Figure 3.1: Stambaugh and Yuan Factor Construction

	Median ME	
	Small High $P1$	Big High $P1$
80th $P1$ percentile		
	Small Neutral $P1$	Big Neutral $P1$
20th $P1$ percentile		
	Small Low $P1$	Big Low $P1$

	Median ME	
	Small High $P2$	Big High $P2$
80th $P2$ percentile		
	Small Neutral $P2$	Big Neutral $P2$
20th $P2$ percentile		
	Small Low $P2$	Big Low $P2$

than that of Fama and French (1993). Specifically, when constructing the SMB factor used in the M-4 model (henceforth, SMB_M), Stambaugh and Yuan compute the return on the small-cap leg as the value-weighted portfolio of stocks present in the intersection of both small-cap middle groups when sorting on size / $P1$ and size / $P2$ (the two Small Neutral portfolios in Figure 3.1), and the short leg as the value-weighted portfolio of stocks in the intersection of the large-cap middle groups (the two Big Neutral portfolios in Figure 3.1). The value of the SMB_M factor in a given month is then computed as the return on the small-cap leg minus the return on the large-cap leg return.

3.2.3 The Composite Mispricing Factor, SMB_{CM}, and $MNOR$

In constructing the UMO factor discussed in Stambaugh and Yuan (2017), I follow the methodology outlined in Stambaugh et al. (2015). The method closely resembles the one outlined in Section 3.2.2, but rather than sorting the anomalies into two clusters, I construct a univariate monthly measure, P, which correlates with the degree of relative mispricing in the cross-section, where P is formed by averaging each stock's rankings with respect to all of the available Stambaugh and Yuan anomaly measures. Similarly to the $MGMT$ and $PERF$ factors, when constructing the mispricing factor, I require that a stock have non-missing data for at least three of the eleven anomalies in order be included in the factors mispricing measure. Furthermore, for an anomaly to be included in its mispricing cluster I require that at least 30 stocks have non-missing values for that anomaly. UMO is then constructed by applying a 2 x 3 sorting scheme on size and relative mispricing (P). The monthly value is calculated as the simple average of the returns of the two low-P

portfolios, less the simple average of the returns of the two high-P portfolios.

Analogous to the construction of SMB_M, when constructing the SMB_{CM} factor, I compute the return on the small-cap leg as the value-weighted portfolio of stocks present in the small-cap middle group when sorting on size and P, and the long leg as the value-weighted portfolio of stocks in the large-cap middle group when sorting on size and P. Finally, I compute the SMB_{CM} factor as the return difference between the long and short legs.

I also construct an adapted composite mispricing factor for the Norwegian market. Although the construction of this factor closely follows the methodology of Stambaugh and Yuan (2017) and Stambaugh et al. (2015), I impose some further restrictions in order for an anomaly to be considered for the adapted factor. Specifically, in order for an anomaly to be included in the adapted Norwegian composite mispricing measure, PA, I require it to produce a positive *and* statistically significant alpha (at the 10 percent level) when running the regression in (5). The motivation for this is simple. As previously noted, averaging across several variables which do not capture systematic risk or mispricing effects might contaminate the factor with extraneous information, by using stricter restrictions I am hoping to capture more robust effects. The anomalies left after imposing these restrictions are investments-to-assets, O-score, momentum, and return on assets. In addition, I also include the liquidity measure of Abdi and Ranaldo (2017) discussed in Section 2.2. The reason for this is that liquidity was found by Næs et al. (2009) to be a significant factor in explaining the expected cross-section of Norwegian stock returns.

The value of the Norwegian univariate relative mispricing measure, PA, is thus calculated as the simple average of investments-to-assets, O-score, momentum, return on assets, and liquidity. Similarly to $MGMT$, $PERF$, and UMO, when constructing the mispricing factor, I require that a stock have non-missing data for at least three of the five anomalies in order be included in the factors mispricing measure. Furthermore, for an anomaly to be included in its mispricing cluster I require that at least 30 stocks have non-missing values for that anomaly. The $MNOR$ factor is then constructed by applying a 2 x 3 sorting scheme on size and the adapted relative mispricing measure (PA), where the monthly value is calculated as the simple average of the returns of the two low-PA portfolios, less the simple average of the returns of the two high-PA portfolios.

3.3 Testing Procedures

3.3.1 Returns of Anomalies and Factors

To explore the relation between average returns and sorting characteristics I use two approaches. First, I calculate the spread of a long-short portfolio long in quintile 1 and short in quintile 5 for each characteristic, then use a standard t-test to test the difference against zero. However, merely looking at the return difference between the extreme portfolios does not allow the conclusion that the returns have a monotonically increasing or decreasing pattern across the five portfolios. Thus, as a second measure, I implement the Patton and Timmermann (2010) test of a Monotonic Relations (MR) between the sorting characteristics and average returns. The MR-test can be specified in two ways, either as a test of monotonically increasing or decreasing returns against the null of a flat relation. I specify the alternative hypothesis to be consistent with the evidence from the U.S., i.e., the alternative hypothesis is formulated to test whether the returns are monotonically decreasing (as sorted) for all anomalies. In addition, I also test for and report the p-values of the MR-Up (+) and MR-Down (-) test from the same study, which account for both the frequency, magnitude, and direction of deviations from a flat pattern.

3.3.2 Empirical Framework for Estimation of Factor Models

Although there are different ways of estimating the factor risk premiums and the models ability to price a set of test assets, this paper implements the method of Black et al. (1972), where one runs time-series regressions of the type,

$$R_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + \varepsilon_{i,t} \tag{6}$$

where $R_{i,t}$ is the excess return on security i at time t, α_i is a constant, and $\beta_{i,k}$ is security i's exposure to risk factor f_k. For the first step regression model performance can be assessed by looking at the absolute size of the estimated intercept. Recall from Section 2.1 that in an unconditional framework the expected excess return of a stock in equilibrium can be expressed as,

$$E[R_i] = \sum_{k} \beta_{i,k} \lambda_k$$

where R_i is the excess return on stock i, $k \in \{1, \ldots, K\}$ are the factors driving returns, $\beta_{i,k}$ is the factor loading (exposure) to factor k, and λ_k is the risk premium of factor k.

This implies that if the model is correctly specified, and thus captures all return variation, its pricing error, α_i, should be zero. In the case with multiple test portfolios and multiple simultaneous regressions, this condition is met if all N regression intercepts are jointly equal to zero, or $\alpha_i = 0 \ \forall \ i \in \{1, \ldots, N\}$. This implication can be tested using the Gibbons et al. (1989) "GRS"-test, which can be stated as,

$$F = \frac{T}{N} \times \frac{T - N - K}{N(T - K - 1)} \times \frac{\hat{\alpha}' \hat{\sum}^{-1} \hat{\alpha}}{1 + \hat{\mu}' \hat{\sigma}^{-1} \hat{\mu}} \sim F(N, T - N - K) \tag{7}$$

where N is the number of test assets, T is the number of months, K is the number of factors in the model, $\hat{\alpha}$ is an $N \times 1$ vector of the estimated intercepts, $\hat{\sum}$ is the estimated residual covariance matrix, $\hat{\mu}$ is an $K \times 1$ vector of the factor portfolios' sample means, and $\hat{\sigma}$ is an estimate of the factor portfolios' covariance matrix. Intercepts significantly different from zero are contrary to the null-hypothesis of jointly insignificant intercepts (pricing errors), thus causing F-value to increase, i.e., in cases where the regression model leads to too many high intercepts in absolute terms, the GRS-test will indicate bad fit. A low F-value indicates that the intercepts are not statistically significant, however, that can either be due to low alphas (i.e., the model fits well in describing average excess returns of the test portfolios) or a large residual covariance matrix (implying that the test has low power to detect mispricing).[25]

[25] See, e.g., Fama and French (2012);Barillas and Shanken (2018).

Data

4.1 Static Sample Restrictions

Although asset pricing data for some of the anomalies discussed in this paper exist for the Norwegian market through the website of Bernt Arne Ødegaard, I have decided to construct all factors from raw data in order for there to be a consistent set of assumptions and restrictions in the security sample. I obtain daily stock prices from the Compustat Global Daily database. The sample comprises of 316 nonfinancial Norwegian firms traded on the Oslo Stock Exchange (OSE). Norwegian firms are defined as companies listed at the OSE with corporate headquarters in Norway. Financial companies are excluded from the sample due to differences in accounting standards and risk profiles relative to operational companies (see e.g. Viale, Kolari, and Fraser, 2009).[26] Many of the companies in the sample also have stocks listed across different share classes (e.g. common, preferred, A-, and B-stocks). In such cases, I compute the market equity of the companies as a weighted average across all common, A- and B-share classes, but identify and compute returns solely on the basis of their primary share class, as identified by the Compustat primary issue tag. Some companies not only have shares listed at Oslo Stock Exchange but also have listings at foreign exchanges. As these listings are merely duplicates of the listings at Oslo Stock Exchange (only converted to the respective local currency), the observations are removed in order to avoid double counting.

Further, I observe a number of delisted companies which have major discrepancies between the observed trade day, the Compustat delisting date, and the official deletion date obtained from Oslo Stock Exchange.[27] In order to rectify this I follow the methodology outlined in Ince and Porter (2006) and remove all observations which have the Compustat price code 5[28] and are occur after the Compustat deletion date and all zero values (with returns calculated from the price index) from the end of the sample until the first non-zero value. Furthermore, as a measure to ensure that I do not remove real observations, I compute the 20-, 40-, and 60-day rolling standard deviation of return, the 20-, 40-, and 60-day

[26] Note that the industry portfolios are formed before the last step of restrictions, i.e., before the removal of financial companies from the sample.

[27] The most notable examples of this are, Norsk Solkraft AS and NetConnect AS, which have no observations for well over a year and where the Compustat deletion date is off by more than 6 months relative to the news bulletins from Oslo Stock Exchange. Other observations go the other way around, the most notable example being Loki ASA, who has sample observations 3 years and 10 months after the official deletion date (which in this case coincides with the Compustat deletion date).

[28] Compustat price code 5 implies that the price of security has simply been carried forward from the last reported value.

mean daily high minus low price spread, and the 20-, 40-, and 60-day rolling mean trading volume in order to check the trading-activity up until the point of deletion.

The impact on the sample due the above restrictions and adjustments can be seen in Table 4.1, which shows the number of firms having survived the different filters, i.e., the number of firms remaining in the sample after each step.

Table 4.1: Evolution of the securities sample after static filtering in a given year J (J = 1996–2018)

Notes: This table shows the number of companies left in the sample in a given year J (J = 1996–2018) after imposing different static restrictions on the sample as discussed in Section 4.1, where the second column (*Sample*) lists the number of companies in the raw sample obtained from the Compustat Global database (including financial companies).

Year	Sample	−Non-Common	−Foreign	−Non-OSE	−Delisted
1996	127	126	126	126	118
1997	122	122	122	122	118
1998	139	139	139	139	136
1999	140	140	140	140	137
2000	155	155	154	153	148
2001	176	176	175	174	172
2002	188	188	187	185	184
2003	181	181	180	178	176
2004	168	168	168	166	164
2005	196	196	194	183	180
2006	225	225	223	191	189
2007	260	260	257	200	199
2008	255	255	252	196	195
2009	242	242	239	183	180
2010	229	229	227	180	179
2011	229	223	221	177	176
2012	226	218	216	174	172
2013	222	214	212	174	173
2014	222	216	214	178	177
2015	215	208	206	170	169
2016	214	207	205	170	170
2017	225	218	215	180	178
2018	231	224	221	184	178

4.2 Dynamic Sample Restrictions

In addition to the static filters applied above, I add an additional layer of dynamic filters in order for a security to be considered for portfolio selection at the end of month t.

As previously noted by Ødegaard (2018) for Oslo Stock Exchange, not all stocks traded at an exchange should necessarily be included when calculating representative empirical asset pricing results. One such example are stocks that are rarely traded. Hence, I follow the method of Ødegaard (2018) and require a stock to have a minimum of 20 trading days in the twelve month period before the end of month t.

It is also common in the asset pricing literature for researchers to remove penny stocks, which typically have market microstructure-issues such as illiquidity and extreme return movements.[29] While Ødegaard (2018) deals with this by filtering out stocks with a price below NOK 10 and a market capitalization of less than NOK 1 million, this would not only have a major impact on my sample size, but I also observe several larger companies that trade below the NOK 10 price mark at different times during the sample period (e.g. due to stock splits). Consequently, in an effort reduce the impact of highly illiquid stocks while preserving the sample size, I require a stock to have either a 12-month rolling mean turnover above the 2.5 percent level in the cross-section or a 12-month rolling mean bid-ask spread below the 97.5 percent level in the cross-section. As daily bid-ask prices are not obtainable through the Compustat database, I use the Abdi and Ranaldo (2017) 2-day corrected spread-measure (Equation 11 in that study), derived from the daily high and low prices obtainable through Compustat.[30] Furthermore, similar to Chordia, Roll, and Subrahmanyam (2000), Amihud (2002), Pastor and Stambaugh (2003), and Lee (2011), I require the stock price at the end of month $t-1$ to be above the 2.5 percent level of the cross-section for the entire sample in order to be included in the sample in month $t-1$.

The developments in sample size after implementing the above measures can be seen in Table 4.2. In Appendix B.1 I also report the impact on the sample size when imposing stricter filters or when using the method proposed by Ødegaard (2018).

4.3 Return Calculations

As Compustat does not provide return data for securities directly, the prices (daily item PRCCD) are adjusted for dividends, splits, and equity offerings using the (cumulative) adjustment factor (daily item ADJEXDI), as well as cash equivalent distributions, reinvestment of dividends and the compounding effect on dividends paid on reinvested dividends through the total return factor (daily item TRFD). Based on the adjusted price I calculate the discrete monthly return for company i at time t as,

[29] For a discussion on the characteristics and pricing behavior of penny stocks, see e.g. Q. Liu, Rhee, and Zhang (2011) and Bhattacharyya and Chandra (2016).

[30] This measure was chosen among a wealth of different options due to its simplicity and accuracy in level estimates, as discussed in Johann and Theissen (2017).

Table 4.2: Evolution of the securities sample after dynamic filtering in a given year J ($J = 1996$–2018)

Notes: This table shows the number of companies left in the sample in a given year J ($J = 1996$–2018) after imposing various dynamic restrictions on the sample, where the second column (*Static*) lists the number of companies left in the sample after the static filtering process described in section 4.1. Columns 3 through 6 show the changes in sample size after imposing the restrictions discussed in Section 4.2, where to be considered for portfolio selection at the end of month $t-1$ a company must: i) have more than 20 trade days in the 12-month period leading up to the end of month $t-1$; ii) have either a 12-month rolling mean turnover above the 2.5 percent level in the cross-section or a 12-month rolling mean bid-ask spread below the 97.5 percent level in the cross-section (as measured by the 2-day corrected spread measure of Abdi and Ranaldo, 2017) leading up to the end of month $t-1$; and iii) a stock price at the end of month $t-1$ above the 2.5 percent level of the cross-section for the entire sample.

Year	**Static**	**−Trading**	**−Illiquidity**	**−Penny**	**−Financials**
1996	118	117	72	72	58
1997	118	118	106	106	89
1998	136	136	118	118	101
1999	137	137	127	127	108
2000	148	147	111	111	96
2001	172	172	126	125	108
2002	184	184	144	141	117
2003	176	176	161	154	120
2004	164	164	143	143	112
2005	180	180	151	151	121
2006	189	189	167	167	135
2007	199	199	173	173	139
2008	195	194	179	179	145
2009	180	180	172	171	137
2010	179	179	161	160	127
2011	176	176	165	164	131
2012	172	172	165	163	130
2013	173	173	161	159	129
2014	177	177	156	155	125
2015	169	169	158	157	126
2016	170	170	161	160	126
2017	178	178	164	163	129
2018	178	178	163	163	126

$$r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$$

where, $P_{i,t} = (PRCCD_{i,t}/ADJEXDI_{i,t}) \times TRFD_{i,t}$.

The risk-free rate of return, r_f, is proxied by the 1-month Norwegian Interbank Offered Rate (NIBOR) obtained from Macrobond. The risk-free rate is the interest rate for borrowing at the given date for a stated period and set to be forward looking.

When constructing the market index I follow the common approach in the literature and derive it as the return on a broad index of domestic stocks, namely all stocks found eligible for portfolio selection in a given month. However, as previously noted by Næs et al. (2009), as the OSE is dominated by a few large companies, using a value-weighted index would mainly reflect the return of a few large companies, thus I follow their approach and construct both equal- and value-weighted market returns.

4.4 Annual and Quarterly Accounting Data and Income Statements

Annual and quarterly accounting and income data are collected from the Compustat Global Database. As some of the companies in my sample report figures in foreign currencies (USD and EUR), I convert all data to NOK. For the currency conversion I obtain daily spot rates for NOK/EUR and NOK/USD from Norges Bank, and calculate 4 different sets of exchange rates: i) annual balance sheet rates, defined as the exchange rate of the last day of company i's fiscal year (as identified by the Compustat variable FYR); ii) quarterly balance sheet rates, defined as the exchange rate of the last day of company i's fiscal quarter (as identified by the compustat variables FYR and FQTR); iii) annual profit and loss exchange rates, defined as the mean of all exchange rates within company i's fiscal year; and iv) quarterly profit and loss exchange rates, defined as the mean of all exchange rates within company i's fiscal quarter.

4.5 Other Sources of Data

Some of the anomalies discussed in this paper rely on the use of index data and/or daily return data. The monthly data for the OSE All-Share Index (OSEAX), used to construct the beta and distress anomalies, are obtained through Macrobond. The daily factor data for the market, SMB, and HML factors, used to estimated the idiosyncratic volatility measure of Ang et al. (2006), are obtained through the website of Bernt Arne Ødegaard.

Results

5.1 Returns

5.1.1 Anomaly Returns

To get an idea of which effects might be present at the Oslo Stock Exchange, I first look at the returns of portfolios formed by a single-sorting process based on the different characteristics discussed in Section 2.2. In the upcoming, I will constrain the discussion to revolve (for the most part) around the significant ones.[31]

As can be seen from Tables 5.3 and 5.4, most of the anomalies fail to produce significant returns both when using an equally-weighted and value-weighted approach. Perhaps most surprisingly, given that both of these anomalies were found to be significant in the study of Næs et al. (2009), both size and liquidity are found not only to be insignificant across both weighting-schemes but also that they produce negative average returns when measured for the full sample period.

We also observe cases in which the anomalies produce significant returns under one of the weighting-schemes but not the other, or when they are significant under both weighting-schemes but more pronounced under one than the other. This is less surprising. Equal-weighted portfolios are typically tilted towards small-cap stocks. Smaller capitalization stocks often have lower liquidity (and are thus more expensive to trade) and have less information available for the market, in other words, they are more difficult to arbitrage, have higher levels of information uncertainty, and, consequently, they are more susceptible to mispricing. Stock issue-anomalies have long been suspected to arise from sentiment driven mispricing (see e.g. Stambaugh, Yu, and Yuan (2012)); net stock issues is significant at the 5 percent level and composite equity issuance at the 1 percent level in the equal-weighted portfolios, but neither are significant in the value weighted portfolios, lending support to mispricing as a culprit.[32] Return on assets is also statistically significant (at the 10 percent level) in the equal-weighted sorts, but fails to produce a significant return in the value-weighted case, consistent with the findings of Wang and Yu (2013), who observe that the anomaly primarily exists among firms with high arbitrage costs and information uncertainty. From the double sorted portfolios shown in Table 5.5, we see that the effects of

[31] Note in the upcoming discussion that the term *significant* is loosely defined and simply implies statistical significance *at least* at the 10 percent level.

[32] Observe in Panel A of Table E.1 in Appendix E that they produce both an economically and statistically significant alpha from the regression in 5 for the equal-weighted case, but fail to do so in the value-weighted case.

Table 5.3: Monthly percentage average returns and standard deviations for one-dimensional, *equal-weighted portfolios*: July 1998 – June 2018 (240 months)

Notes: This table shows average monthly returns and standard deviations for equally weighted portfolios formed on different characteristics using OSE-quintiles. Portfolios are rebalanced monthly. The portfolios for the ROA- and Distress-anomaly runs from October 2004 and July 2005, respectively. Portfolios are sorted such that a high quintile is associated with a low future return in the literature. The overall-column shows the return difference of a portfolio long in quintile 1 and short in quintile 5 along with (in parenthesis) its t-statistic of a mean different than zero test. The MR t-statisic is the Monotonic Relationship test of Patton and Timmermann (2010), where I test if average returns are monotonically strictly decreasing (as sorted) against the null of a flat relation. In addition I report the Up (+) and Down (-) p-values with a null of a flat pattern, with the alternative that at least some parts of the pattern are increasing / decreasing. *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

		Quintiles						Overall		
		1 (low)	2	3	4	5 (high)	Spread (1-5)	MR (t-stat)	p-value (+)	p-value (-)
Beta	Return	0.85	0.81	1.08	0.87	0.80	0.06	0.12	0.70	0.68
	Std.Dev	4.54	5.60	6.44	7.87	9.26	(0.12)			
Size	Return	0.38	0.97	0.96	0.99	0.97	-0.59	-1.53	0.44	0.98
	Std.Dev	7.52	7.02	6.62	6.59	6.62	(-1.44)			
BM	Return	0.69	0.78	1.22	0.60	1.06	-0.37	-0.75	0.06	0.20
	Std.Dev	8.45	6.16	6.10	6.11	7.21	(-0.87)			
Liquidity	Return	0.40	1.03	1.10	1.11	0.77	-0.36	-0.78	0.36	0.65
	Std.Dev	8.36	7.79	7.06	5.92	4.78	(-0.90)			
IVOL	Return	1.04	1.37	1.06	0.80	0.34	0.70*	1.76**	0.70	0.10*
	Std.Dev	5.39	7.48	7.25	7.34	8.34	(1.79)			
NSI	Return	1.10	1.21	1.05	0.49	0.23	0.95**	2.46***	0.89	0.06*
	Std.Dev	5.88	6.42	6.64	7.71	8.41	(2.39)			
Accruals	Return	1.16	0.85	0.86	0.78	0.77	0.39	1.33	0.99	0.68
	Std.Dev	7.83	5.71	6.46	6.85	6.93	(1.18)			
NOA	Return	0.98	0.89	0.80	0.91	0.81	0.18	0.47	0.94	0.75
	Std.Dev	7.43	6.93	6.27	6.57	7.05	(0.47)			
Asset Growth	Return	0.81	1.34	1.08	0.50	0.64	0.18	0.50	0.26	0.03**
	Std.Dev	8.00	6.35	5.91	5.89	7.56	(0.45)			
ITA	Return	0.92	0.95	0.90	1.20	0.39	0.53*	1.65**	0.67	0.08*
	Std.Dev	7.03	6.91	6.64	6.14	6.85	(1.74)			
Distress	Return	1.05	0.59	1.05	0.31	1.13	-0.08	-0.20	0.02	0.02**
	Std.Dev	5.53	5.68	6.45	6.66	6.93	(-0.21)			
O-score	Return	1.22	1.07	0.92	0.85	0.30	0.91**	2.35***	0.98	0.10*
	Std.Dev	6.21	5.76	6.46	6.65	8.44	(2.47)			
GPP	Return	0.93	1.28	0.77	0.53	0.52	0.41	1.11	0.71	0.14
	Std.Dev	5.93	7.00	6.41	7.01	7.86	(1.07)			
ROA	Return	1.47	1.37	1.04	0.30	0.67	0.80*	1.65**	0.73	0.01***
	Std.Dev	5.20	4.90	5.15	6.17	7.76	(1.81)			
CEI	Return	1.42	1.20	0.89	0.56	0.33	1.09***	2.47***	0.98	0.03**
	Std.Dev	8.98	7.02	5.81	5.01	7.19	(2.62)			
Momentum	Return	2.06	1.39	0.67	0.25	-0.07	2.12***	4.28***	0.96	0.00***
	Std.Dev	6.73	5.23	6.19	6.97	9.27	(4.54)			

Table 5.4: Monthly percentage average returns and standard deviations for one-dimensional, *value-weighted portfolios*: July 1998 – June 2018 (240 months)

Notes: This table shows average monthly returns and standard deviations for value weighted portfolios formed on different characteristics using OSE-quintiles. Portfolios are rebalanced monthly. The portfolios for the ROA- and Distress-anomaly runs from October 2004 and July 2005, respectively. Portfolios are sorted such that a high quintile is associated with a low future return in the literature. The overall-column shows the return difference of a portfolio long in quintile 1 and short in quintile 5 along with (in parenthesis) its t-statistic of a mean different than zero test. The MR t-statisic is the Monotonic Relationship test of Patton and Timmermann (2010), where I test if average returns are monotonically strictly decreasing (as sorted) against the null of a flat relation. In addition I report the Up (+) and Down (-) p-values with a null of a flat pattern, with the alternative that at least some parts of the pattern are increasing / decreasing. *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

Characteristic		Quintiles					Overall			
		1 (low)	2	3	4	5 (high)	Spread (1-5)	MR (t-stat)	p-value (+)	p-value (-)
Beta	Return	1.26	0.93	0.96	1.07	0.37	0.89*	1.84**	0.92	0.09*
	Std.Dev	4.88	6.60	6.67	7.62	9.50	(1.77)			
Size	Return	0.33	0.99	0.90	1.02	0.91	-0.58	-1.53	0.23	0.82
	Std.Dev	7.10	6.92	6.69	6.69	5.98	(-1.47)			
BM	Return	0.60	1.35	1.21	0.42	0.67	-0.07	-0.12	0.20	0.12
	Std.Dev	9.05	7.14	6.21	6.06	8.66	(-0.13)			
Liquidity	Return	0.42	0.79	0.87	0.97	0.89	-0.47	-0.81	0.63	0.94
	Std.Dev	10.05	8.43	7.03	6.66	5.87	(-0.80)			
IVOL	Return	1.05	1.19	0.81	0.84	-0.48	1.53***	2.50***	0.92	0.08*
	Std.Dev	5.69	8.02	8.70	9.21	10.27	(2.84)			
NSI	Return	0.91	1.13	1.04	0.76	0.75	0.18	0.33	0.78	0.66
	Std.Dev	6.38	6.55	7.14	9.30	9.50	(0.33)			
Accruals	Return	1.55	0.98	0.71	0.70	0.70	0.85	1.37	0.99	0.34
	Std.Dev	10.07	6.68	7.41	6.50	7.51	(1.57)			
NOA	Return	1.40	1.02	1.30	0.65	0.94	0.46	0.64	0.37	0.21
	Std.Dev	12.38	7.58	6.84	6.67	6.01	(0.65)			
Asset Growth	Return	1.05	1.34	0.84	0.78	0.48	0.57	1.31	0.86	0.17
	Std.Dev	8.55	7.11	6.26	6.48	9.11	(1.28)			
ITA	Return	1.42	0.78	0.63	1.11	0.54	0.88**	2.51***	0.53	0.02**
	Std.Dev	7.22	6.98	7.01	7.05	7.80	(2.13)			
Distress	Return	0.96	0.88	1.24	1.20	0.94	0.02	0.03	0.78	0.80
	Std.Dev	6.44	6.25	6.78	7.92	7.72	(0.04)			
O-Score	Return	1.02	0.99	0.62	0.43	0.09	0.92*	1.62*	0.98	0.21
	Std.Dev	6.01	6.44	7.71	7.90	10.32	(1.74)			
GPP	Return	1.25	0.63	0.90	0.97	0.60	0.65	1.60*	0.77	0.13
	Std.Dev	7.76	8.44	7.14	6.77	7.06	(1.59)			
ROA	Return	1.40	1.51	0.70	0.51	0.71	0.69	1.28	0.90	0.11
	Std.Dev	6.17	6.57	5.87	7.69	8.81	(1.19)			
CEI	Return	1.08	1.02	0.59	0.79	0.72	0.36	0.70	0.89	0.45
	Std.Dev	9.64	8.16	7.15	5.69	7.11	(0.72)			
Momentum	Return	1.46	0.99	0.86	0.27	0.07	1.40**	2.36***	0.98	0.03**
	Std.Dev	7.83	6.28	7.00	7.81	10.87	(2.27)			

the ROA-anomaly are stronger in small- and mid-cap companies than large-cap. However, from the other sorts the effect is not so clear.

Smaller companies are also typically more volatile and have higher bankruptcy risk, this is consistent with the observation that the O-score effect is more robust in the equal-weighted sorts. From Table 5.5 we see that the O-score is especially strong when paired with beta, IVOL, ITA, and momentum. The momentum effect is strong and robust in both sorts, however it is clearly stronger and more robust in the equal-weighted case (observe the 60 bps per month outperformance of the long leg in the equal-weighted sorts over the value-weighted sorts in Tables 5.3 and 5.4). This could be due to the previously mentioned rebalancing effect, where one sells high and take new broad positions in momentum winners, but the performance gap raises suspicions that something more is afoot. Turning to the double sorted portfolios in Table 5.5, we see that the momentum returns are strongest in small- and mid-cap companies, with high O-scores, medium and high betas, low return on assets, and are decreasing in liquidity. For example, a portfolio long in illiquid momentum winners and short in illiquid momentum losers delivers a return spread of 2.33 percent per month, corresponding to an annualized return of 31.76 percent, whereas a portfolio long in liquid momentum winners and short in liquid momentum losers delivers a return spread of 0.86 percent per month, corresponding to an annualized return of 10.86 percent. Although consistent with mispricing, past momentum winners seems to outperform momentum losers without exception and no matter the second sorting criterion. This is an indication that the momentum effect might be more robust in the Norwegian market than previously reported by Næs et al. (2009) and Nygaard (2011).

The IVOL-anomaly is both more pronounced and robust in the value-weighted portfolios than in the equal-weighted portfolios.[33] The largest IVOL-spread is obtained by constructing a portfolio long in low ITA / IVOL and short in high ITA / IVOL, second only to the momentum-liquidity portfolio it delivers a return spread of 2.16 percent per month, equivalent to an annualized return of 29.28 percent. Investment-to-assets is also stronger in the value-weighted case, and especially strong among large-cap stocks, or combined in a portfolio with low beta, low O-score, and low IVOL.

Finally, the relation between beta and return in Table 5.3 is essentially flat, whereas it is monotonically decreasing and significant at the 10 percent level in the Table 5.4.[34] The

[33]This is somewhat similar to the finding of Bali and Cakici (2008), who observe that a negative relation between risk and return in value-weighted portfolios when measuring IVOL using daily data and CRSP-breakpoints, but no relation when using an equal-weighted approach.

[34]Although not very robust, this is not clear evidence against the anomaly per see; as argued in a series of articles by Arnott, Beck, Kalesnik, and West (2016), Arnott, Beck, and Kalesnik (2016a, 2016b), Arnott et al. (2019), many investors assume that the low beta factor implies that low beta stocks outperforms high

Table 5.5: Monthly Percentage Average Returns and t-statistics for Two-Dimensional, Value-Weighted Portfolios: July 1998 – June 2018 (240 Months)

Notes: This table shows the monthly percentage average returns and t-statistics for various independently sorted, value-weighted portfolios based on tertile breakpoints (3 x 3). The portfolios sorted on the return on assets anomaly runs from October 2004.

	Return (Mean)			t-statistic		
	Low	Neutral	High	Low	Neutral	High
			Panel I: Size / Momentum			
Big	0.40	0.89	1.13	0.65	2.06	2.45
Medium	-0.21	1.32	1.84	-0.35	2.62	3.83
Small	0.06	0.90	1.74	0.11	2.33	3.95
			Panel II: Size / Idiosyncratic Volatility			
Big	1.04	0.64	0.60	2.83	1.19	0.64
Medium	0.20	1.23	0.40	0.34	2.12	0.77
Small	1.35	1.14	0.07	3.41	2.31	0.14
			Panel III: Size / Beta			
Big	1.35	0.89	0.55	3.48	2.21	0.98
Medium	0.71	1.19	0.59	1.90	1.98	0.80
Small	0.82	0.97	0.79	2.39	1.97	1.36
			Panel IV: Size / Investments-to-Assets			
Big	1.37	0.90	0.80	2.84	2.02	1.72
Medium	0.41	1.38	0.74	0.79	2.68	1.31
Small	0.95	0.85	0.78	2.08	1.82	1.70
			Panel V: Size / O-Score			
Big	0.99	0.75	0.18	2.63	1.67	0.26
Medium	0.88	0.65	0.27	1.31	1.26	0.54
Small	1.23	1.03	0.49	2.68	2.51	0.83
			Panel VI: Size / Illiquidity			
Big	1.16	0.61	0.81	2.92	1.41	1.08
Medium	0.78	0.65	0.82	1.97	1.11	1.38
Small	1.09	1.44	0.30	2.86	2.93	0.56
			Panel VII: Size / Return on Assets			
Big	1.02	1.28	0.99	1.45	2.57	2.16
Medium	0.15	1.37	1.57	0.25	3.00	3.21
Small	0.74	0.50	1.60	1.22	1.00	3.46
			Panel VIII: Idiosyncratic Volatility / Momentum			
High	-0.28	0.50	1.46	-0.34	0.98	2.08

Table 5.5 continued from previous page

	Return (Mean)			t-statistic		
	Low	Neutral	High	Low	Neutral	High
Medium	0.10	1.03	1.05	0.15	2.37	2.37
Low	0.29	0.74	1.58	0.44	1.34	3.04
Panel IX: Idiosyncratic Volatility / Investments-to-Assets						
High	0.72	0.78	-0.53	1.11	1.02	-0.76
Medium	1.24	1.08	0.91	2.98	2.52	1.99
Low	1.63	0.47	0.76	2.32	0.90	1.29
Panel X: Idiosyncratic Volatility / O-Score						
High	0.43	0.51	-0.42	0.60	0.78	-0.58
Medium	1.06	0.91	0.41	2.80	2.21	0.73
Low	0.95	0.48	0.82	1.73	0.93	1.21
Panel XI: Idiosyncratic Volatility / Beta						
High	0.82	0.83	-0.40	1.75	1.14	-0.49
Medium	1.28	0.83	0.77	3.33	2.03	1.48
Low	0.81	1.21	0.41	2.04	2.30	0.64
Panel XII: Idiosyncratic Volatility / Return on Assets						
High	0.44	0.38	0.45	0.53	0.58	0.68
Medium	0.87	1.35	0.98	1.47	2.64	2.10
Low	0.95	1.01	1.21	1.36	1.68	2.17
Panel XIII: Investments-to-Assets / Momentum						
High	0.08	1.01	1.09	0.13	1.94	2.03
Medium	0.28	0.95	1.60	0.41	2.14	3.06
Low	0.22	1.11	1.06	0.31	2.39	2.25
Panel XIV: Investments-to-Assets / O-Score						
High	0.86	0.71	-0.09	1.72	1.52	-0.14
Medium	1.29	1.21	0.55	2.90	2.26	0.78
Low	1.12	0.94	-0.05	2.13	1.88	-0.07
Panel XV: Investments-to-Assets / Beta						
High	0.78	1.04	0.24	1.86	2.14	0.39
Medium	1.12	0.82	1.10	2.88	1.87	1.75
Low	1.18	1.15	0.48	3.06	2.46	0.78
Panel XVI: Investments-to-Assets / Illiquidity						
High	0.85	0.35	0.13	2.16	0.66	0.20
Medium	0.91	1.27	1.45	2.05	2.68	2.12
Low	1.20	1.07	0.28	2.63	2.16	0.42

Table 5.5 continued from previous page

	Return (Mean)			t-statistic		
	Low	Neutral	High	Low	Neutral	High
Panel XVII: Investments-to-Assets / Return on Assets						
High	0.49	0.99	0.61	0.68	1.69	1.10
Medium	1.30	1.20	1.75	1.88	2.20	3.69
Low	-0.08	1.10	1.05	-0.11	2.22	1.91
Panel XVIII: O-Score / Momentum						
High	-0.62	0.21	1.53	-0.90	0.38	1.94
Medium	0.67	0.90	1.29	1.00	2.09	3.04
Low	0.47	0.79	1.20	0.68	1.74	2.55
Panel XIX: O-Score / Beta						
High	0.25	0.46	-0.14	0.53	0.75	-0.17
Medium	1.18	0.88	0.72	2.97	2.12	1.28
Low	1.51	0.40	0.80	3.51	0.90	1.13
Panel XX: O-Score / Illiquidity						
High	0.44	0.39	0.98	0.81	0.58	1.22
Medium	1.01	0.63	0.37	2.43	1.35	0.56
Low	0.45	1.32	0.40	1.09	2.71	0.66
Panel XXI: O-Score / Return on Assets						
High	0.52	0.05	-0.21	0.71	0.08	-0.28
Medium	1.42	1.47	0.99	1.89	2.67	2.05
Low	0.83	0.76	1.17	1.20	1.53	2.22
Panel XXII: Illiquidity / Momentum						
High	-0.40	0.17	1.93	-0.54	0.28	3.02
Medium	0.09	0.76	1.29	0.16	1.81	3.01
Low	0.28	0.93	1.14	0.44	1.93	2.42
Panel XXIII: Illiquidity / Beta						
High	0.49	0.26	0.87	1.03	0.42	1.13
Medium	1.23	1.09	1.05	2.78	2.71	1.79
Low	1.29	0.82	0.23	3.42	1.76	0.40
Panel XXIV: Illiquidity / Idiosyncratic Volatility						
High	0.91	0.86	0.74	1.35	1.29	0.95
Medium	1.07	1.42	0.19	2.68	2.54	0.36
Low	0.99	0.44	-0.05	2.22	0.84	-0.07
Panel XXV: Illiquidity / Return on Assets						
High	0.66	0.40	0.55	0.79	0.64	0.82

Table 5.5 continued from previous page

	Return (Mean)			*t*-statistic		
	Low	Neutral	High	Low	Neutral	High
Medium	0.84	1.24	1.25	1.26	2.62	2.50
Low	0.51	0.93	1.01	0.79	1.70	1.88
Panel XXVI: Beta / Momentum						
High	-0.53	0.52	1.22	-0.73	0.90	1.92
Medium	-0.70	0.88	1.58	-1.06	2.10	3.98
Low	0.31	1.51	0.79	0.53	3.72	1.61
Panel XXVII: Beta / Return on Assets						
High	0.53	1.21	0.93	0.78	2.12	1.72
Medium	1.03	1.49	1.27	1.52	3.58	2.82
Low	0.47	0.66	1.05	0.66	1.30	1.95
Panel XXVIII: Return on Assets / Momentum						
High	0.80	1.11	1.26	1.16	2.02	2.59
Medium	0.07	0.42	1.88	0.08	0.77	2.49
Low	0.09	1.15	2.04	0.16	2.24	3.70

long leg of the beta anomaly clearly outperforms the short leg in several of the sorts in Table 5.5 (e.g. in large-caps), however it seems to be dominated to some extent by some of the other anomalies, such as momentum and liquidity.

5.1.2 Factor Returns

Starting from the top in Table 5.6, we observe that the value-weighted market-factor slightly outperforms the equal-weighted market-factor, both in the case of raw returns and risk-adjusted returns (Sharpe ratio). This echoes the observation from Tables 5.3 and 5.4, where the size factor is negative, i.e., large-cap outperforms small-cap over the whole sample period. We also see that the SMB-factors and (consistent with, e.g., Næs et al., 2009) the HML-factor produce small and insignificant returns. The LIQ-factor, although not statistically significant, produces a substantial negative mean monthly return. However, this might be due to the choice of proxy for liquidity.[35] All of the mispricing factors

beta stocks. This is not (necessarily) the case. The main benefit of the low beta factor is risk reduction. They also argue that a significant portion of the alpha earned by the factor thus far has been due to a rise in relative valuation: where low beta stocks used to trade at a deep discount they now trade at a substantial premium.

[35] There are at least three reasons which can influence the results in regards to the liquidity anomaly and LIQ-factor: i) the fact that I am using a different proxy for liquidity than Næs et al. (2009); ii) that

produce significant returns at least at the 5 percent level, however, the UMO and $MNOR$ factors have both notably lower standard deviations and higher monthly returns. In regards to the strong performance of the $MNOR$-factor, one could of course argue that this is (at least in part) due to an element of data mining, seeing that the factor is constructed on the basis of the most robust in-sample anomalies. Observe also in Table F.4 of Appendix F, that the $MNOR$ and UMO factors are (due to their similarity in construction) relatively strongly correlated, with a correlation coefficient of 0.51. Nevertheless, it is interesting to observe that all of the mispricing factors of Stambaugh and Yuan (2017) are significant at least at the 5 percent level.

Table 5.6: Monthly Percentage Average Returns, t-statistics, and Summary Statistics for Factor Portfolios: July 1998 – June 2018 (240 Months)

This table shows (percentage) mean monthly returns, along with their summary statistics and t-statistic of a mean different than zero test for equally-weighted factor portfolios formed on: the SMB and HML factors of Fama and French (1993); the SMB_{CM}, SMB_M, UMO, $MGMT$, and $PERF$ factors of Stambaugh and Yuan (2017); the $MNOR$ factor discussed in Section 3.2.3; the LIQ factor of Næs, Skjeltorp, and Ødegaard (2009), proxied by the Abdi and Ranaldo (2017) 2-day corrected spread estimator; as well as the equal- and value-weighted market factor measured in excess of the 1-month NIBOR. *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Return (mean)	**Std.Dev**	**t-stat**	**Median**	**25th percentile**	**75th percentile**
$RMRF$	0.64*	5.88	1.69	0.93	-2.83	4.26
$RMRF_{EW}$	0.58	6.15	1.45	1.16	-2.62	4.25
SMB	0.33	3.96	1.30	0.53	-2.02	2.71
SMB_{CM}	0.16	5.18	0.47	-0.32	-2.91	2.45
SMB_M	-0.04	4.74	-0.13	0.00	-2.81	2.30
HML	0.36	5.35	1.04	0.37	-2.92	3.63
UMO	1.44***	6.24	3.57	1.15	-1.74	5.35
$MGMT$	1.18**	8.52	2.15	0.70	-2.63	5.47
$PERF$	1.09**	8.10	2.08	0.91	-2.99	5.92
$MNOR$	1.85***	6.42	4.47	2.09	-1.58	4.96
LIQ	-0.60	6.52	-1.44	-0.92	-4.17	2.75

5.1.3 CAPM-Adjusted Returns

When comparing the returns of the different factors and anomalies it is useful to put them on equal risk levels. Thus, inspired by Arnott et al. (2019), I standardize the anomaly-

the bid-ask spread is not a very effective proxy for liquidity (assuming the bid-ask spread is generally decreasing over time); and/or iii) that the Abdi and Ranaldo (2017) spread has some measurement error as it is a proxy for the bid-ask spread in itself.

spreads and factors to have an annualized volatility of 10% for the upcoming discussion. I also create equal-weighted portfolios of factors for the different models discussed in Section 3.2. Specifically, FF-3 is a portfolio long in the market, SMB and HML factor; the M-3 portfolio is long in the market, SMB_{CM} and UMO factors; the M-4 portfolios is long in the market, SMB_M, $MGMT$, and $PERF$ factors; the NOR portfolios is long in the market, SMB, and $MNOR$ factors; and the NSO portfolios is long in the market, SMB, and LIQ factors. The same risk scaling is applied to the factor portfolios, however this is done in two steps. First I scale the individual factors to have an annualized volatility of 10%, then I create the equally weighted portfolios and rescale them to 10% annualized volatility.[36]

In Table 5.7, I report the mean annualized return of all anomalies (value-weighted), factors, and factor-portfolios discussed throughout this paper (collectively, the factors), as well as the CAPM-adjusted returns. As we have already seen, the most of the factors analyzed delivers positive returns, the exceptions being the size, book-to-market, liquidity, SMB_M, and LIQ. On the right hand side of the table, we see that out of the anomalies beta, ITA, O-score, GPP, and momentum produce positive and significant CAPM-alphas. A more surprising finding is that the IVOL-anomaly (marginally) fails to produce a significant CAPM-alpha. In other words, only 5 out of the 16 anomalies produce significant alphas across the whole sample period, i.e., cannot be explained by the CAPM. Moreover, only 3 out of the 9 factors and 2 out of the 5 portfolios of factors statistically outperforms the market factor across the whole sample period. However, we also observe that some of the factors, namely beta; investment-to-assets; UMO; $PERF$; and $MNOR$ have a combination of a positive and significant alpha and a negative and significant beta, which implies potential diversification benefits for investors. Finally, in the factor-portfolios we see the diversification benefits in the form of higher returns and t-statistics at the same risk-levels. This is due to the relatively low correlation between the individual factors in each portfolio, reported in Appendix F.

5.1.4 Monthly Returns Conditional on Market Performance and Business Cycles

Table 5.8 reports return performance conditional on market performance and economic cycles. The right hand side of the table report the mean monthly returns in months of market upturn and months of market downturn (defined as more than one standard devia-

[36]Note that the portfolios that best represent the models would be the mean-variance efficient combination of the factors that enter the models, not equal-weight. Although the approach of scaling the individual securities to have equal volatility prior to equal weighting is similar in spirit, it does not take into account correlations between factors and differences in mean returns

Table 5.7: Mean Annualized Factor Returns and CAPM-Adjusted Returns, OSE: July 1998 – June 2018

Notes: This table shows the mean annualized returns and the CAPM-alpha's (in percentage), the CAPM-beta's, as well as the accompanying t-statistics for the researched factors. The market factors are measured in excess of the 1-month NIBOR. The anomaly factors (Beta:Momentum) are value weighted, zero investment portfolios based on OSE-quintiles (long 1, short 5), sorted such that a high quintile is associated with a low future return in the literature. All factors are scaled to 10 percent (annualized) volatility. The portfolios of factors are equally weighted averages of the factors included in the respective models and also scaled to 10 percent volatility. Values marked in bold have corresponding t-statistics in excess of 3.0 in absolute value. *** Denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

Factor	**Mean Annualized Return**	***t*-stat**	**CAPM Alpha**	**CAPM Alpha *t*-stat**	**CAPM Beta**	**CAPM Beta *t*-stat**
$RMRF$	3.84*	1.69				
$RMRF_{EW}$	3.30	1.45				
Beta	4.04*	1.77	4.24**	2.26	**-0.46*****	-8.02
Size	-3.24	-1.47	-4.09*	-1.78	**-0.35*****	-4.80
BM	-0.28	-0.13	-1.12	-0.42	-0.03	-0.41
Liquidity	-1.77	-0.80	-3.09	-1.43	0.06	0.88
IVOL	6.55***	2.84	3.92	1.63	0.07	0.94
NSI	0.76	0.33	-1.74	-0.69	-0.04	-0.48
Accruals	3.57	1.57	1.91	1.02	**0.22*****	3.74
NOA	1.46	0.65	2.31	1.34	-0.15***	-2.87
Asset Growth	2.90	1.28	2.88	1.19	-0.14*	-1.89
ITA	4.86**	2.13	5.35*	1.84	-0.21**	-2.41
Distress	0.10	0.04	0.64	0.23	-0.13	-1.45
O-Score	3.97*	1.74	5.24**	2.11	-0.05	-0.66
GPP	3.61	1.59	5.77**	2.13	-0.06	-0.68
ROA	3.24	1.19	3.55	1.22	-0.06	-0.64
CEI	1.62	0.72	-1.69	-0.70	0.21***	2.79
Momentum	5.19**	2.27	5.68**	2.07	-0.07	-0.83
SMB	2.95	1.30	3.20	1.39	**-0.47*****	-6.65
SMB_{CM}	1.05	0.47	0.03	0.01	**-0.38*****	-5.01
SMB_{M}	-0.30	-0.13	-1.17	-0.48	**-0.45*****	-5.89
HML	2.35	1.04	-0.97	-0.43	-0.04	-0.52

Table 5.7 continued from previous page

Factor	Mean Annualized Return	t-stat	CAPM Alpha	CAPM Alpha t-stat	CAPM Beta	CAPM Beta t-stat
UMO	**8.29*****	3.57	**11.19*****	4.57	**-0.29*****	-4.01
$MGMT$	4.92**	2.15	2.78	1.06	-0.03	-0.38
$PERF$	4.76**	2.08	4.6*	1.80	-0.20***	-2.62
$MNOR$	**10.47*****	4.47	**14.29*****	5.21	**-0.34*****	-4.17
LIQ	-3.16	-1.44	-4.90**	-2.16	0.09	1.18
FF-3	6.52***	2.83	1.54	0.63	**0.35*****	4.58
M-3	**9.05*****	3.89	**7.49*****	3.78	**0.22*****	3.73
M-4	**7.71*****	3.33	3.55	1.40	0.18**	2.34
NOR	**13.01*****	5.50	**12.93*****	5.53	0.14**	2.07
NSO	1.99	0.88	-1.04	-0.51	**0.35*****	5.37

tion above and below the mean of a value-weighted index, respectively), as well as months of market neutrality (between ± one standard deviation from the mean of a value-weighted index). The left hand side of the table reports the mean returns across the Norwegian business cycles. The data for the Norwegian business cycles is obtained from the Federal Reserve Bank of St. Louis and is defined such that the recession begins midpoint of the period of the peak and ends midpoint of the period of the trough.[37] With the exception of investment-to-assets, composite equity issuance, and $MGMT$, all of the significant factors we have looked at thus far perform poorly when the market does great, performs great when the market falls, and delivers positive returns when the market moves sideways. The premiums under the cycle regimes are, however, more mixed. Only IVOL, O-score, UMO, and $MNOR$ of the factors we have discussed, along with the M-3 and NOR factor-portfolios, delivers a positive and significant return premium during recessions out of the anomalies we have discussed. This, of course, is not surprising, given that they are constructed to short sell companies with high degrees of idiosyncratic volatility, bankruptcy risk, and/or mispricing, respectively.

[37]The Federal Reserve Bank of St. Louis publish business cycle data for numerous countries across the globe and can be downloaded from FRED Economic Data: https://fred.stlouisfed.org/categories/32262

Table 5.8: Mean Monthly Factor Returns Conditional on Market Performance and Economic Cycles: July 1998 – June 2018

Notes: This table shows the mean (percentage) monthly returns for the researched factors conditional on different market conditions. Down months are defined as months with a market return more than 1 standard deviation below the (value-weighted) mean; up months are defined as months with a market return more than 1 standard deviation above the (value-weighted) mean; the Norwegian business cycle data is obtained from the Federal Reserve Bank of St. Louis and is defined such that the recession begins midpoint of the period of the peak and ends midpoint of the period of the trough. The market factors are measured in excess of the 1-month NIBOR. The anomaly factors (Beta:Momentum) are value weighted, zero investment portfolios based on OSE-quintiles (long 1, short 5), sorted such that a high quintile is associated with a low future return in the literature. All factors are scaled to 10 percent (annualized) volatility. The portfolios of factors are equally weighted averages of the factors included in the respective models and also scaled to 10 percent volatility. Values marked in bold have corresponding t-statistics in excess of 3.0 in absolute value. *** Denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

	Market Return			Business Cycles	
Factor	**Up**	**Neutral**	**Down**	**Expansion**	**Recession**
$RMRF$	**3.56*** **	**0.51*** **	**-3.99*** **	**0.68*** **	-0.09
$RMRF_{EW}$	**4.55*** **	**0.40*** **	**-4.69*** **	0.65***	-0.15
Beta	**-2.27*** **	0.25	**3.36*** **	0.33	0.34
Size	1.11**	-0.41*	-0.94*	-0.24	-0.31
BM	0.29	-0.14	0.30	-0.11	0.07
Liquidity	2.42***	-0.37**	-1.57***	-0.21	-0.08
IVOL	-0.99**	0.59***	1.72***	0.57**	0.49*
NSI	-1.14**	0.11	1.03	0.26	-0.14
Accruals	1.55*	0.08	0.18	0.36	0.22
NOA	2.18**	0.01	-1.33**	0.03	0.22
Asset Growth	-0.15	0.23	0.70	0.14	0.35
ITA	1.09**	0.21	0.67	0.34	0.46
Distress	-0.81	-0.01	0.70	0.03	-0.01
O-Score	**-1.87*** **	0.26	**2.84*** **	0.09	0.58*
GPP	0.98*	0.36*	-0.73	0.32	0.27
ROA	**-2.11*** **	0.5**	0.40	0.29	0.24
CEI	1.72**	0.03	-0.93	0.09	0.19
Momentum	-1.15	**0.61*** **	1.03**	0.51**	0.33
SMB	0.97	0.07	0.45	0.22	0.26

Table 5.8 continued from previous page

	Market Return			Business Cycles	
Factor	**Up**	**Neutral**	**Down**	**Expansion**	**Recession**
SMB_{CM}	**2.09*****	-0.12	-0.83	0.08	0.09
SMB_M	1.49**	-0.21	-0.57	0.07	-0.13
HML	-0.09	0.08	1.06*	0.41*	-0.04
UMO	-0.35	**0.71*****	1.45**	0.55**	0.79***
$MGMT$	**2.41*****	0.20	-0.54	0.47*	0.32
$PERF$	**-2.25*****	0.47**	**2.58*****	0.53**	0.23
$MNOR$	-0.46	**0.89*****	**1.82*****	0.6**	**1.09*****
LIQ	**2.11*****	-0.32*	**-2.35*****	-0.41*	-0.11
FF-3 Portfolio	**3.12*****	0.47**	**-1.74*****	**0.92*****	0.09
M-3 Portfolio	**3.60*****	**0.75*****	**-2.29*****	**0.89*****	0.54*
M-4 Portfolio	**3.00*****	0.56***	**-1.45*****	**1.01*****	0.19
NOR Portfolio	**3.00*****	**1.08*****	-1.27**	**1.11*****	**0.93*****
NSO Portfolio	**3.77*****	0.15	**-3.34*****	0.28	0.04

It is also worth nothing that many of the factors appears to have higher returns in one state than the other, observe for example that both of the market factors have lower absolute returns in up states than down states, both of which are far above the market neutral state, implying that their distributions are negatively skewed and leptokurtic (have positive excess kurtosis, also known as fat tails), i.e., not normally distributed.[38] Table G.1 in Appendix G shows us that this is indeed the case, where all but one of the factors (distress) can be said to be leptokurtic and many of the factors have a considerable degree of excess kurtosis, in other words extreme return realizations are not infrequent.[39]

Table 5.8 also show that most of the factors appears to be negatively correlated with

[38]Skewness measures the asymmetry in (return) distributions, where a negatively (positively) skewed distribution has more large negative (positive) outliers than large positive (negative) outliers of the same magnitude. The excess kurtosis paints an image of the fatness of the tails, i.e., the extent to which we observe extreme realizations in both directions. A normal distribution has a skewness of 0 and an excess kurtosis of 0 (kurtosis of 3).

[39]Observe also that the momentum returns are negative in up states, which is consistent with the findings of Daniel and Moskowitz (2016), who observe momentum crashes which occur in panic states, following market declines and when market volatility is high, and are contemporaneous with market rebounds. However, the skewness and excess kurtosis of momentum in Table G.1 lends little support to these findings, where momentum appears (without formal testing) to be more normal than most of the considered anomalies.

the market, looking at the correlations between the factors and the excess market return confirms that this is indeed the case.[40] The fact that such a wide range of factors have correlations that are apparently negatively correlated with the excess market return is remarkable, but not unexpected. The anomalies that delivers the highest and most significant returns in times of market downturns are beta, IVOL, O-score, and momentum, i.e., portfolios with a substantial proportion of companies with high past return, low volatility relative to the market, low idiosyncratic volatility, and high past return, commonly referred to as *quality* stocks. The fact that they pay off in bad states is consistent with a flight-to-quality effect. Moreover, we observe a positive relation between excess market return and liquidity and LIQ, consistent with a flight-to-liquidity effect.

5.2 Assessing Model Fit

Table 5.9 reports alphas from the different factor models for all of the long-short anomaly spreads discussed in this paper but idiosyncratic volatility.[41] Unsurprisingly, the FF-3 model produces the most economically and statistically significant alphas among the anomalies (consistent with the fact that many of them have been found anomalous in the regression in 5). More surprisingly, the NSO model have the largest number of minimum absolute alphas with 7 (rising to 9 if we exclude NOR). The results are, however, generally mixed, and none of the models have a clear edge in accommodating the anomalies (even if we restrict ourselves only to look at the sub-set of anomalies analyzed by Stambaugh and Yuan). Observe, however, that both beta and size produces statistically and economically significant alphas, whereas only the NOR and NSO (and, on the margin M-3) models seem to accommodate the momentum anomaly, rendering the momentum alpha insignificant.

As is common in empirical asset pricing,[42] Table 5.10 reports comparative statistics on several measures which summarize the models abilities to accommodate the set of anomaly spreads discussed in this paper (again, except idiosyncratic volatility): average absolute alpha, the Gibbons et al. (1989) "GRS" test of whether all alphas equal zero along with its accompanying p-value, and the average adjusted R^2. Panels A and B report statistics corresponding to that of Panel A in Table 5 of Stambaugh and Yuan (2017). As the return series on the ROA and distress anomalies start at a later date than the others, Panel A (and C) reports these measures for the set of 10 (13) anomalies analyzed by Stambaugh and Yuan

[40]The correlation tables for both equal- and value-weighted anomaly-returns, correlation of factor returns, rank correlations of factors returns, and rolling 12-month correlations of the factor portfolios are reported in Appendix F and H.1.

[41]For the accompanying factor loadings, see Tables J.1 through J.5 in Appendix J.1. Appendix J.2 also reports the factor loadings for industry portfolios.

[42]See, for example, Fama and French (2015)Hou et al. (2015)Stambaugh and Yuan (2017).

Table 5.9: Anomaly Alphas Under Different Factor Models, From July 1998 Through June 2018 (240 months)

Notes: For all anomalies but idiosyncratic volatility, this table reports measures of alpha computed under five different factor models: i) the three-factor model of Fama and French (1993), denoted FF-3; ii) the three-factor composite mispricing model of Stambaugh and Yuan (2017), denoted M-3; iii) the four-factor mispricing model of Stambaugh and Yuan (2017), denoted M-4; iv) the three-factor Norwegian composite mispricing model, denoted NOR; and v) the three-factor model of Næs, Skjeltorp, and Ødegaard (2009), denoted NSO. In constructing the long-short spreads, the long leg is the value-weighted portfolio of stocks in the lowest quintile of the anomaly measure, and the short leg contains the stocks in the highest quintile, where a high value of the measure is associated with lower return. The breakpoints are based on OSE quintiles. Panel A reports the monthly alphas (in percent); Panel B reports their heteroskedasticity-consistent t-statistics based on White (1980). The sample period runs from July 1998 through June 2018 for all but the distress and ROA anomalies, which run from July 2005 through June 2018.

Anomaly	FF-3	M-3	M-4	NOR	NSO
Panel A: Alphas					
Beta	1.26	1.45	1.10	1.26	0.93
Size	1.58	1.66	1.19	1.61	1.17
BM	0.65	0.64	0.74	0.27	0.58
NSI	0.71	0.30	0.30	0.16	0.50
Accruals	0.20	-0.49	-0.20	0.10	0.54
NOA	1.63	0.89	0.69	0.57	1.31
Asset Growth	-0.88	-0.90	-0.47	-1.30	-0.10
ITA	-0.85	-0.62	-0.37	-0.59	-0.64
Distress	-0.52	0.32	0.44	0.83	-0.12
O-score	0.38	0.30	-0.13	0.46	0.00
GPP	0.56	0.11	0.20	0.64	0.67
ROA	0.16	-0.77	0.07	-0.81	0.65
CEI	0.44	0.50	0.66	0.54	0.39
Momentum	0.76	0.68	0.85	0.56	0.63
Liquidity	0.18	-0.08	-0.13	-0.13	0.03
Panel B: t-statistics					
Beta	3.07	3.44	2.80	2.96	2.37
Size	3.45	3.90	2.81	3.46	2.55
BM	1.58	1.48	1.69	0.66	1.36
NSI	1.93	0.86	0.80	0.44	1.32
Accruals	0.40	-1.02	-0.40	0.21	1.04
NOA	2.77	1.50	1.19	0.98	2.21

Table 5.9 continued from previous page

Anomaly	FF-3	M-3	M-4	NOR	NSO
Asset Growth	-1.60	-1.58	-0.88	-2.46	-0.21
ITA	-2.67	-2.03	-1.30	-1.61	-1.91
Distress	-1.14	0.60	0.88	1.69	-0.23
O-score	0.71	0.57	-0.24	0.89	-0.01
GPP	1.08	0.23	0.41	1.18	1.10
ROA	0.27	-1.34	0.10	-1.37	0.95
CEI	1.00	1.07	1.45	1.14	0.86
Momentum	1.93	1.65	2.07	1.37	1.55
Liquidity	0.62	-0.29	-0.45	-0.45	0.09

(2017) (in this paper), running from July 1998 through June 2018. Panel B (and D) reports these measures for the full set of 12 anomalies (all but IVOL) analyzed by Stambaugh and Yuan (2017) (in this paper) starting in July of 2005 and running through June 2018. The left-hand-side of the table reports these measures for value-weighted anomaly portfolios versus a value-weighted market factor, whereas the right-hand-side reports measurements for equal-weighted anomaly portfolios versus an equal-weighted market factor (following Næs et al. (2009)).

In Panel A we see that both in the equal- and value-weighted case the M-4 model has the smallest average absolute alpha and, on average, explains most of the return variance in the anomalies. However, looking at the GRS-statistics we see that all of the models, except NOR, are rejected at the 1 percent level. In Panel B, we see that the composite mispricing models produce the smallest average absolute alpha in both the equal- and value-weighted case. Moreover, in the value-weighted case, M-3 and NOR produce a p-value of 0.11 and 0.14, respectively. In other words, at a significance level of 11% and 14% or less, the GRS test does not reject the hypothesis that all of the 12 sub-sample anomalies are accommodated by these models.[43] When expanding the set of anomalies, in Panels C and D, the results only marginally changes and the results largely corresponds between the two full-sample periods (Panels A and C) and sub-sample periods (Panels B and D). However, some observations can still be made: i) except for the difference between the case of equal-weighted portfolios in Panels A and C, most models have an increase in their mean absolute pricing error; ii) their F-value generally drops; and iii) they explain more of the return variance. Moreover, we observe a difference between the value-weighted and equal-

[43] Recall from Section 3.3.2, however, that although a low F-value (with a corresponding high p-value) indicates that the intercepts are not statistically significant, this can either be due to low alphas or a large residual covariance matrix. Where the latter implies low power.

Table 5.10: Abilities of Models CAPM, FF-3, M-3, M-4, NOR, and NSO to Accommodate Different Groups of Test Assets, From July 1998 Through June 2018 (240 months)

Notes: This table reports measures that summarizes to which degree different groups of test assets produce alpha under five different factor models: the CAPM of Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966), denoted CAPM; the three-factor model of Fama and French (1993), denoted FF-3;the three-factor mispricing model of Stambaugh and Yuan (2017), denoted M-3; the four-factor mispricing model of Stambaugh and Yuan (2017), denoted M-4; the three-factor Norwegian mispricing model, denoted NOR; and the three-factor model of Næs, Skjeltorp, and Ødegaard (2009), denoted NSO. For each model and test asset group, the table reports the average absolute alpha $A|\alpha_i|$, the F-statistic and associated p-value for the GRS-test of Gibbons, Ross, and Shanken (1989), and the average adjusted R-squared, $A(\text{adj. } R^2)$. The left-hand side of the table reports these summary statistics for value weighted test assets versus a value weighted market factor, while the right-hand side of reports the statistics for equally weighted test assets versus an equal weighted market factor. Panel A reports statistics for OSE-sorted BM; NSI; accruals; NOA; asset growth; ITA; O-score; GPP; CEI; and momentum for the full sample period. Panel B summarizes statistics for the same anomalies as Panel A, in addition to the distress and ROA anomalies from July 2005 through June 2018. Panel C reports statistics for OSE-sorted beta; size; BM; NSI; accruals; NOA; asset growth; ITA; O-score; GPP; CEI; momentum; and liquidity for the full sample period. Panel C summarizes statistics for the same anomalies as Panel A, in addition to the distress and ROA anomalies from July 2005 through June 2018.

	Value-Weighted				*Equal-Weighted*			
Model	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)
Panel A: 10 Anomaly Portfolios, July 1998 – June 2018								
CAPM	0.62	2.78	2.98E-03	0.03	0.78	5.99	4.90E-08	0.06
FF-3	0.67	3.13	9.33E-04	0.12	0.83	6.25	2.10E-08	0.16
M-3	0.63	2.55	0.01	0.13	0.60	4.28	1.82E-05	0.15
M-4	0.50	2.33	0.01	0.18	0.58	4.37	1.35E-05	0.17
NOR	0.63	2.27	0.02	0.11	0.61	3.99	4.96E-05	0.14
NSO	0.60	2.73	3.46E-03	0.13	0.78	6.03	4.38E-08	0.12
Panel B: 12 Anomaly Portfolios, July 2005 – June 2018								
CAPM	0.58	2.24	0.01	0.02	0.72	4.59	2.91E-06	0.07
FF-3	0.59	2.42	0.01	0.10	0.72	4.85	1.18E-06	0.17
M-3	0.47	1.55	0.11	0.12	0.41	2.56	4.28E-03	0.16
M-4	0.57	2.21	0.01	0.16	0.56	3.85	4.30E-05	0.20
NOR	0.47	1.49	0.14	0.12	0.55	2.67	2.94E-03	0.17
NSO	0.52	2.20	0.01	0.12	0.75	4.84	1.23E-06	0.14
Panel C: 13 Anomaly Portfolios, July 1998 – June 2018								
CAPM	0.69	2.87	7.54E-04	0.06	0.73	4.35	1.57E-06	0.10
FF-3	0.76	3.01	4.30E-04	0.16	0.78	4.62	5.08E-07	0.21
M-3	0.72	2.94	5.63E-04	0.18	0.59	3.16	2.26E-04	0.19

Table 5.10 continued from previous page

	Value-Weighted				*Equal-Weighted*			
Model	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)
M-4	0.55	2.50	3.34E-03	0.22	0.52	3.23	1.70E-04	0.22
NOR	0.73	2.41	4.61E-03	0.15	0.62	3.02	4.09E-04	0.19
NSO	0.60	2.53	2.96E-03	0.20	0.71	4.47	9.23E-07	0.18
Panel D: 15 Anomaly Portfolios, July 2005 – June 2018								
CAPM	0.73	2.16	0.01	0.05	0.89	3.78	1.33E-05	0.09
FF-3	0.77	2.28	0.01	0.13	0.89	3.99	5.62E-06	0.19
M-3	0.50	1.50	0.11	0.16	0.59	2.14	0.01	0.19
M-4	0.64	2.09	0.01	0.20	0.70	3.20	1.56E-04	0.22
NOR	0.48	1.46	0.13	0.14	0.69	2.48	2.90E-03	0.19
NSO	0.61	2.02	0.02	0.16	0.90	3.84	1.07E-05	0.17

weighted case: the mean absolute pricing errors and model performances are generally better when looking at value-weighted portfolios, but the models generally explain more of the return variance of the equal-weighted portfolios. Nevertheless, apart from the value-weighted case with M-3 and NOR in Panel B, as well as, the value-weighted case with M-3, NOR, and NSO in Panel D, all models are rejected at the 1 percent level by the GRS-test in every other sorting.

Following Stambaugh and Yuan (2017) I also test for and report whether the factors unique to one model produce non-zero alphas with respect to another model, in other words to which extent a model can price the factors of the others. Contrary to Stambaugh and Yuan (2017), who uses both the frequentist approach applied here and a Bayesian approach, I have limited the analysis to only include a frequentist approach. Table 5.11 reports the alphas and corresponding t-statistics in Panel A, as well as the GRS statistic, the accompanying p-value, and the adjusted R^2 in Panel B. I also report the statistics for the CAPM in the first column of the table.

We see that all models, except the NOR model, clearly spans the HML-factor. The M-4 model also does a reasonably good job of explaining the LIQ-Factor, which both of the other mispricing models fail to accommodate. The NOR model is the only model able to price the UMO (although the M-4 model explains more of the return variation), which is not surprising given the relatively high correlation between the factors (see Table F.4); both of the composite mispricing models does a good job accommodating the $MGMT$ and $PERF$ factors of the M-4 model; whereas none of the models appears able to accommodate the $MNOR$ factor.

Table 5.11: Abilities of Models CAPM, FF-3, M-3, M-4, NOR, and NSO to Explain Each Other's Factors

Notes: This table reports a factor's estimated monthly alpha (in percent) with respect to each of the other models with White (1980) heteroskedasticity-consistent t-statistics in parentheses (Panel A). In Panel B I compute the Gibbons, Ross, and Shanken (1989) F-test of whether a given model produces zero alphas for the factors of an alternative model, along with the associated p-values and the adjusted R-squared. The market and size factors are not considered. The factors are tested against the CAPM of Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966), denoted CAPM; the three-factor model of Fama and French (1993), denoted FF-3, which include the HML factor;the three-factor mispricing model of Stambaugh and Yuan (2017), denoted M-3, which include the UMO factor; the four-factor mispricing model of Stambaugh and Yuan (2017), denoted M-4, which includes the MGMT and PERF factors; the three-factor Norwegian mispricing model, denoted NOR, which include the MNOR factor; and the three-factor model of Næs, Skjeltorp, and Ødegaard (2009), denoted NSO, which include the LIQ factor. The sample period is from July 1998 through June 2018 (240 months).

	Alpha computed with respect to model					
Factors	CAPM	FF-3	M-3	M-4	NOR	NSO
	Panel A: Alpha (t-statistic)					
Factors in FF-3						
HML	0.43		0.60	0.46	0.85	0.30
	(1.26)		(1.75)	(1.34)	(2.44)	(0.87)
Factors in M-3						
UMO	1.55	1.62		0.85	0.56	1.72
	(3.96)	(4.40)		(2.31)	(1.66)	(4.47)
Factors in M-4						
MGMT	1.06	0.90	-0.07		0.32	1.24
	(2.06)	(1.76)	(-0.13)		(0.53)	(2.55)
PERF	1.38	1.66	0.85		0.77	1.24
	(2.77)	(3.54)	(1.81)		(1.66)	(2.74)
Factors in NOR						
MNOR	2.00	2.19	1.26	1.46		2.20
	(4.91)	(5.60)	(3.41)	(3.60)		(5.31)
Factors in NSO						
LIQ	-0.82	-0.94	-1.20	-0.67	-1.27	-
	(-2.08)	(-2.38)	(-3.2)	(-1.94)	(-3.21)	-

Panel B: GRS F-statistic, p-value, adj. R^2

Table 5.11 continued from previous page

		Alpha computed with respect to model					
Factors		CAPM	FF-3	M-3	M-4	MNOR	NSO
HML	F-stat	1.57		2.89	1.68	5.59	0.74
	p-value	0.21		0.09	0.20	0.02	0.39
	adj. R^2	0.02		0.03	0.03	0.06	0.05
UMO	F-stat	14.88	16.00		6.17	2.24	17.90
	p-value	1.48E-04	8.46E-05		0.01	0.14	3.33E-05
	adj. R^2	0.02	0.04		0.33	0.26	0.05
$MGMT$, $PERF$	F-stat	5.57	6.73	1.81		1.45	5.30
	p-value	4.34E-03	1.44E-03	0.17		0.24	0.01
	adj. R^2	0.06	0.12	0.33		0.19	0.20
$MNOR$	F-stat	23.95	29.48	11.64	14.42		28.10
	p-value	1.83E-06	1.40E-07	7.58E-04	1.86E-04		2.64E-07
	adj. R^2	0.04	0.10	0.28	0.20		0.06
LIQ	F-stat	4.12	5.84	9.59	3.48	9.51	
	p-value	0.04	0.02	2.20E-03	0.06	2.29E-03	
	adj. R^2	0.09	0.18	0.22	0.33	0.17	

Following the recommendation of Lewellen et al. (2010), Appendix I also reports these measures when the models are tested on industry portfolios and various double sorted portfolios. Although most models fare better than in the tests for anomaly portfolios, the results again vary across test assets and weighting schemes, and no model can be said to dominate across the wide range of test assets.

5.3 Arbitrage Risk and the Factor Models

As argued by Stambaugh et al. (2015) and Stambaugh and Yuan (2017), since higher idiosyncratic volatility implies greater arbitrage risk, there should be more mispricing present among stocks with high idiosyncratic volatility. Among overpriced (underpriced) stocks, the relation between idiosyncratic volatility and alpha should therefore be negative (positive), as arbitrage eliminates less overpricing (underpricing) in high-IVOL stocks. However, with arbitrage asymmetry, the negative relation among overpriced stocks should be stronger, resulting in the overall negative relation between alpha and IVOL (the idiosyncratic volatility anomaly). Both Stambaugh et al. (2015) and Stambaugh and Yuan (2017) report results consistent with the above predictions. Thus, in this section I investigate the relation between idiosyncratic volatility and mispricing for the Norwegian market.

Table 5.12 shows double sorted, value-weighted porfolio returns formed on the composite mispricing measure of Stambaugh and Yuan (2017) and IVOL, as well as double sorted, value-weighted portfolio returns formed on the Norwegian composite mispricing measure and IVOL. Strikingly, none of the return spreads in Panel A are significant at any conventional level, and only the underpriced portfolio with low IVOL delivers a statistically significant return. Panel B, on the other hand, delivers economically and statistically significant spreads in both the short overpriced/high-IVOL, long underpriced/high-IVOL portfolio and the short overpriced/high-IVOL, long overpriced/low-IVOL case. Again, I emphasize that the PA measure has an element of data mining going on. However, it might still be the case that there is an relation between IVOL and mispricing, only that the P measure might be contaminated with extraneous information due to averaging over several insignificant anomalies (as discussed in Section 3.2.2). Although not formally tested, I also note that returns of overpriced stocks appear to be monotonically decreasing in IVOL, whereas there seems to be a flat relation in underpriced stocks, consistent with arbitrage asymmetry.

Table 5.12: Double Sorted Portfolios on Composite Mispricing and Idiosyncratic Volatility

Notes: This table show the mean (percentage) monthly returns, returns spreads, and accompanying t-statistics (in parenthesis) for independently sorted, value-weighted portfolios based on OSE tertile breakpoints (3 x 3), on the composite mispricing measure of Stambaugh and Yuan (2017), P, and idiosyncratic volatility in Panel A, as well as the Norwegian composite mispricing measure PA and idiosyncratic volatility in Panel B. The sample period runs from July 1998 through June 2018.

	Low IVOL	Medium	High IVOL	Spread (L-H)
Panel A: Composite Mispricing / IVOL				
Overpriced	0.59	0.10	-0.04	0.63
	(1.37)	(0.17)	(-0.05)	(0.86)
Underpriced	1.06	0.63	0.91	0.15
	(2.47)	(1.12)	(1.29)	(0.25)
Spread (U-O)	0.47	0.52	0.95	
	(1.25)	(0.94)	(1.11)	
Panel B: Norwegian Composite Mispricing / IVOL				
Overpriced	0.67	0.07	-0.69	1.36
	(1.41)	(0.11)	(-0.87)	(1.97)
Underpriced	1.13	0.85	1.12	0.01
	(2.53)	(1.44)	(1.53)	(0.02)
Spread (U-O)	0.46	0.78	1.80	
	(1.06)	(1.42)	(2.03)	

Table 5.13 report alphas with accompanying t-statistics for the value-weighted, double sorted portfolios adjusted for the each of the factor models. We see that the FF-3 model has the largest absolute pricing error in the extreme overpriced / high-IVOL portfolio, which is to be expected due to the construction of both the composite mispricing and IVOL measures.[44] A more surprising finding, however, is that the NSO model has the smallest absolute pricing error in the extreme overpriced / high-IVOL portfolio. Nevertheless, turning to Table 5.14 which report the GRS test statistics of the same sortings,[45] we see that, especially the M-4 model, but that the M-3 model also has a lower mean absolute pricing error (alpha) and explains slightly more of the return variation than the other models. However, none of the models are rejected (note, again, this does not necessarily imply that they are a good fit).

[44] See Section 3.2.3 and Appendix A for details on the construction of P and IVOL, respectively.

[45] GRS test statistics for the double sorted portfolios on PA and IVOL are reported in Panel F of Table I.1 in Appendix I.

Table 5.13: Effects of Idiosyncratic Volatility in Under- versus Overpriced Stocks

Notes: This table shows the monthly percentage alphas and t-statistics on value weighted portfolios formed by an independent 3 x 3 sort on the composite mispricing measure of Stambaugh and Yuan (2017) and the idiosyncratic volatility measure of Ang, Hodrick, Xing, and Zhang (2006) for each of the five models. The most overpriced stocks are those in the top third of the mispricing measure and the most underpriced stocks are those in the bottom third. Panel A reports alphas for the three-factor model of Fama and French (1993); Panel B reports alphas with respect to the M-3 model of Stambaugh and Yuan (2017); Panel C reports alphas for the M-4 model of Stambaugh and Yuan (2017); Panel D reports alphas with respect to the Norwegian mispricing model; Panel E reports alphas for the 3-factor model of Næs, Skjeltorp, and Ødegaard (2009). The t-statistics on the right are heteroskedasticity consistent based on White (1980). The sample period runs from July 1998 through June 2018 (240 months).

	Alphas			t-statistics		
	Low IVOL	Med. IVOL	High IVOL	Low IVOL	Med. IVOL	High IVOL
			Panel A: FF-3 Model			
Most Overpriced	-0.32	-1.08	-1.36	-1.07	-2.43	-2.05
Most Underpriced	0.14	-0.36	-0.33	0.66	-0.92	-0.57
			Panel B: M-3 Model			
Most Overpriced	-0.06	-0.81	-0.76	-0.21	-1.85	-1.10
Most Underpriced	0.25	-0.45	-0.70	1.01	-1.14	-1.26
			Panel C: M-4 Model			
Most Overpriced	-0.06	-0.81	-0.76	-0.21	-1.85	-1.10
Most Underpriced	-0.07	-0.60	-0.32	-0.23	-1.42	-0.53
			Panel D: NOR Model			
Most Overpriced	-0.24	-0.73	-0.93	-0.78	-1.57	-1.53
Most Underpriced	0.25	-0.52	-1.05	1.05	-1.34	-1.81
			Panel E: NSO Model			
Most Overpriced	-0.26	-0.75	-0.58	-0.88	-1.67	-0.88
Most Underpriced	0.09	-0.36	-0.09	0.44	-0.83	-0.16

Table 5.14: Abilities of Models CAPM, FF-3, M-3, M-4, NOR, and NSO to Accommodate Mispricing and Idiosyncratic Volatility, From July 1998 Through June 2018 (240 months).

Notes: This table reports measures that summarizes to which portfolios independently sorted 3 x 3 on the mispricing measure of Stambaugh and Yuan (2017) and the idiosyncratic volatility measure of Ang, Hodrick, Xing, and Zhang (2006) produce alpha under five different factor models: the CAPM of Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966), denoted CAPM; the three-factor model of Fama and French (1993), denoted FF-3;the three-factor mispricing model of Stambaugh and Yuan (2017), denoted M-3; the four-factor mispricing model of Stambaugh and Yuan (2017), denoted M-4; the three-factor Norwegian mispricing model, denoted NOR; and the three-factor model of Næs, Skjeltorp, and Ødegaard (2009), denoted NSO. For each model, the table reports the average absolute alpha, $A|\alpha_i|$, the F-statistic and associated p-value for the GRS-test of Gibbons, Ross, and Shanken (1989), and the average adjusted R-squared, $A(\text{adj. } R^2)$. The right-hand side of the table reports these summary statistics for value weighted test assets versus a value weighted market factor, while the left-hand side of reports the statistics for equally weighted test assets versus an equal weighted market factor.

	Value Weighted				*Equal Weighted*			
	$A\|\alpha_i\|$	F-stat	p-value	$A(\text{adj. } R^2)$	$A\|\alpha_i\|$	F-stat	p-value	$A(\text{adj. } R^2)$
CAPM	1.68	0.10	0.35	0.50	1.79	0.07	0.38	0.50
FF-3	1.85	0.06	0.40	0.52	2.28	0.02	0.42	0.54
M-3	1.26	0.26	0.49	0.56	1.35	0.21	0.49	0.56
M-4	0.96	0.47	0.34	0.56	1.02	0.42	0.36	0.57
NOR	1.57	0.13	0.61	0.53	1.86	0.06	0.61	0.55
NSO	1.50	0.15	0.32	0.55	1.87	0.06	0.39	0.55

Concluding Remarks and Further Research

Over the past decades, researchers have identified numerous patterns in average stock returns are seemingly at odds with the efficient market hypothesis, giving rise to an ever increasing number of proposed factor models. However, researchers debate both the consistency and even existence of these anomalies, where, for instance, their performances have been found hard to replicate, they have failed to be significant in out-of-sample testing, and their premiums have been found to vanish during some time periods. Moreover, the sources of their abnormal returns have also been called into questions. Where some argue that any characteristic able to predict return must represent a risk factor, others argue that the returns arise from suboptimal behavior of the average investor. Whoever is right, the proliferation of anomalies remained unexplained by the CAPM and three-factor model of Fama and French (1993) is making the need for an alternative factor model, which can accommodate a wider range of anomalies, increasingly clear.

6.1 Conclusion

The primary objective of this paper is to evaluate the applicability of the mispricing models of Stambaugh and Yuan (2017) to the Norwegian stock market in the period between July 1998 and June 2018. The Stambaugh and Yuan models are evaluated against the three-factor model of Fama and French (1993), the three-factor model proposed by Næs et al. (2009), as well as an adapted mispricing model for the Norwegian market. Additionally, I seek to ascertain the presence (or absence) of a wide range of prominent anomalies from the international asset pricing literature in the Norwegian market.

The main finding of this study is that all of the mispricing factors are found to deliver economically and statistically significant returns. Of the other factors only a value-weighted market factor is found to be significant at any conventional levels, as opposed to previous research by Næs et al. (2009), who find that both the SMB-factor of Fama and French, 1993 and a LIQ-factor are significant in describing cross-sectional return differences. However, I note that in the case of the liquidity-factor this might be due to measurement error. Another significant finding is the evidence of a strong momentum effect in the Norwegian market. Returns are observed to be monotonically increasing in momentum, and a portfolio long in past momentum winners and short in past momentum losers survives adjustments to both the CAPM, FF-3, M-3, and M-4 models, but fail to do so for the NSO and NOR models. Moreover, returns are found to be monotonically decreasing in both idiosyncratic volatility, O-Score, and investment-to-assets in both equal- and value-weighted, one-dimensional portfolio sorts. Contrary to the findings of Næs et al. (2009), I find little evidence in support of a size and liquidity effect.

When assessing model fit the results are more mixed and seemingly dependant on both the weighting scheme and choice of test assets, where the latter is a point which has also been made by Lewellen et al. (2010). When applying a goodness of fit test, none of the models are consistently able to accommodate a wide range of anomalies across the full sample period, although the M-3 and NOR models seem able to explain broad sets of value-weighted anomaly portfolios in sub-periods. Results are also mixed for other test assets such as industry portfolios and various double sorted portfolios. When testing the models abilities to accommodate each others factors, all models except NOR is found to span the HML-factor unique to FF-3. M-4 also does a reasonably good job in accommodating the LIQ-factor, whereas neither the NSO nor FF-3 models are able to accommodate any of the mispricing factors. Finally, both Stambaugh et al. (2015) and Stambaugh and Yuan (2017) argue that since higher idiosyncratic volatility implies greater arbitrage risk, there should be more mispricing present among stocks with high idiosyncratic volatility. Moreover, with arbitrage asymmetry, the negative relation should be stronger among overpriced stocks. I find some evidence of arbitrage asymmetry in double-sorted portfolios on mispricing and idiosyncratic volatility, and even though none of the models are rejected by the GRS-test, both of the Stambaugh and Yuan models do a better job in accommodating the IVOL-anomaly, where the M-4 model, in particular, delivers a clearly lower mean absolute pricing error than the other models.

6.2 Further Research

The meaningfulness of these results can still be questioned in several ways, particularly in regards to the limitations of the study, and all of the following aspects give rise to future research possibilities and can used to revise the findings of this study.

Although the primary objective of this thesis has been assess the applicability of the mispricing models of Stambaugh and Yuan (2017) by replicating their study, there are some aspects of their study which have been excluded. As previously noted, in addition to the clustering method used in this paper, Stambaugh and Yuan also apply a cross-sectional approach where they compute the z-score of each stock's anomaly ranking. This is followed by computing and 11 x 11 matrix of average correlations between the respective z-scores, which they then use to calculate the distance measure of Ahn et al. (2009) and form clusters by way of the clustering method of Ward (1963).

I have also limited the replication by only using the widely applied frequentist approach when judging the models' abilities to explain each others factors, where Stambaugh and Yuan also applies a Bayesian approach. The practise of using cross-sectional R^2s and pricing errors to judge the success of models have been critiqued by Lewellen et al. (2010), who show that the explanatory power of many previously documented factors are spurious.

Moreover, Stambaugh and Yuan test the models in their paper against the sentiment index of Baker and Wurgler (2006). As far as I know, there is no version of this index which could easily and meaningfully be applied for the Norwegian market at the moment of writing this thesis.[46] Consequently, testing the models against the sentiment index is left for future research.

Finally, in analyzing the performances of the the anomaly and factor portfolios, trading costs are not taken into account. Several studies find that introducing trading costs to test paper portfolios renders many anomalies returns insignificant, especially those with high monthly turnover (see, e.g., Korajczyk and Sadka, 2004; Novy-Marx and Velikov, 2016). One could expect that implementing trading costs would see the returns of, for example, the momentum effect decrease.

[46] For example, one of the measures included in the sentiment index of Baker and Wurgler (2006) is the closed-end fund discount. Having scoured both the Thomson Reuters Datastream database and Macrobond, I have been unable to find any active closed-end funds in Norway at the time of writing.

References

Abdi, F. & Ranaldo, A. (2017). A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices. *Review of Financial Studies*, *30*(12), 4437–4480.

Acharya, V. V. & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*, 375–410.

Ahn, D.-H., Conrad, J., & Dittmar, R. F. (2009). Basis Assets. *The Review of Financial Studies*, *22*(12), 5133–5174.

Ali, A., Hwang, L.-S., & Trombleya, M. A. (2003). Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics*, *69*, 355–373.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 31–56.

Amihud, Y. & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*, 223–249.

Ang, A. (2014). *Asset Management: A Systematic Approach to Factor Investing*. Oxford University Press.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, *51*, 259–299.

Arnott, R., Beck, N., & Kalesnik, V. (2016a). Timing 'Smart Beta' Strategies? Of Course! Buy Low, Sell High! *Research Affiliates Publications*.

Arnott, R., Beck, N., & Kalesnik, V. (2016b). To Win with 'Smart Beta' Ask If the Price Is Right. *Research Affiliates Publications*.

Arnott, R., Beck, N., Kalesnik, V., & West, J. (2016). How Can "Smart Beta" Go Horribly Wrong? *Research Affiliates Publications*.

Arnott, R., Harvey, C. R., Kalesnik, V., & Linnainmaa, J. (2019). Alice's Adventures in Factorland: Three Blunders That Plague Factor Investing. *Working Paper*.

Artmann, S., Finter, P., Kempf, A., Koch, S., & Theissen, E. (2012). The Cross-Section of German Stock Returns: New Data and New Evidence. *Schmalenbach Business Review*, *64*(1), 20–43.

Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as limits to arbitrage: understanding the low volatility anomaly. *Financial Analysts Journal*, *67*(1), 40–54.

Baker, M. & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*, 1645–1680.

Bali, T. G. & Cakici, N. (2008). Idiosyncratic Volatility and the Cross Section of Expected Returns. *The Journal of Financial and Quantitative Analysis*, *43*(1), 29–58.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

Barberis, N. & Xiong, W. (2012). Realization utility. *Journal of Financial Economics*, *104*(2), 251–271.

Barillas, F. & Shanken, J. (2018). Comparing asset pricing models. *The Journal of Finance*, *73*(2), 715–754.

Barroso, P. & Santa-Clara, P. (2016). Momentum has its moments. *Journal of Financial Economics*, *116*, 111–120.

Basu, S. (1977). Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance*, *32*(3), 663–682.

Basu, S. (1983). The relationship between earnings yield, market value and return for NYSE common stocks: Further evidence. *The Journal of Financial Economics*, *12*(1), 129–156.

Bhattacharyya, A. & Chandra, A. (2016). The Cross-Section of Expected Returns on Penny Stocks: Are Low-Hanging Fruits Not-So Sweet? *Working Paper*.

Black, F. (1993). Beta and Return. *Journal of Portfolio Management*, *20*(1), 8–18.

Black, F. (1972). Capital Market Equilibrium with Restricted Borrowing. *The Journal of Business*, *45*(3), 444–455.

Black, F., Jensen, M. C., & Scholes, M. (1972). The Capital Asset Pricing Model: Some Empirical Tests, in M. Jensen, ed.: *Studies in the Theory of Capital Markets*.

Blitz, D. & Vliet, P. v. (2007). The Volatility Effect: Lower Risk Without Lower Return. *Journal of Portfolio Management*, *34*(1), 102–113.

Brennan, M. J., Cheng, X., & Li, F. (2012). Agency and Institutional Investment. *European Financial Management*, *18*(1), 1–27.

Brennan, M. J. & Subrahmanyam, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, *41*, 441–464.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance*, *63*, 2899–2939.

Capaul, C., Rowley, I., & F., S. W. (1993). International Value and Growth Stocks. *Financial Analysts Journal*, *49*(1), 27–36.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*, 57–82.

Chan, K. C., Chen, N.-f., & Hsieh, D. A. (1985). An exploratory investigation of the firm size effect. *Journal of Financial Economics*, *14*, 451–471.

Chan, K., Hameed, A., & Wilson, T. (2000). Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis*, *35*(2), 153–172.

Chen, L., Novy-Marx, R., & Hsieh, D. A. (2010). An alternative three-factor model. *working paper.*

Chen, N.-f. (1981). Arbitrage asset pricing: Theory and evidence. *Unpublished doctoral dissertation.*

Chen, N.-f. (1982). Some empirical tests of the theory of arbitrage pricing. *Journal of Finance*, *38*, 1393–1414.

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in Liquidity. *Journal of Financial Economics*, *56*, 3–28.

Cochrane, J. H. (2005). *Asset Pricing: Revised Edition.* Princeton University Press.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset Growth and the Cross-Section of Stock Returns. *The Journal of Finance*, *43*(4), 1609–1651.

Corwin, S. A. & Schultz, P. (2012). A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. *The Journal of Finance*, *67*(2), 719–760.

Daniel, K. & Moskowitz, T. J. (2016). Momentum Crashes. *Journal of Financial Economics*, *122*(2), 221–247.

Daniel, K. & Titman, S. (1998). Characteristics or Covariances. *The Journal of Portfolio Management*, *24*(4), 24–33.

Daniel, K. & Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance*, *52*, 1–33.

Daniel, K. & Titman, S. (2006). Market reactions to tangible and intangible information. *The Journal of Finance*, *61*, 1605–1643.

Davis, J. L., Fama, E. F., & French, K. R. (2000). Characteristics, Covariances, and Average Returns: 1929 to 1997. *The Journal of Finance*, *55*(1), 389–406.

Dimson, E. & Marsh, P. (1999). Murphy's law and market anomalies. *Journal of Portfolio Management*, *25*(2), 53–69.

Easley, D., Hvidkjaer, S., & O'Hara, M. (2002). Is Information Risk a Determinant of Asset Returns? *The Journal of Finance*, *57*(5), 2185–2221.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*, 383–417.

Fama, E. F. & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.

Fama, E. F. & French, K. R. (2008). Dissecting Anomalies. *The Journal of Finance*, *63*(4), 1653–1678.

Fama, E. F. & French, K. R. (1997). Industry Costs of Equity. *The Journal of Financial Economics*, *43*(2), 153–193.

Fama, E. F. & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance*, *51*(1), 55–84.

Fama, E. F. & French, K. R. (2006). Profitability, investment, and average returns. *Journal of Financial Economics*, *82*, 491–518.

Fama, E. F. & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance*, *50*, 131–156.

Fama, E. F. & French, K. R. (2012). Size, Value, and Momentum in International Stock Returns. *Journal of Financial Economics*, *105*, 457–472.

Fama, E. F. & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465.

Fama, E. F. & French, K. R. (1998). Value versus Growth: The International Evidence. *The Journal of Finance*, *53*(6), 1975–1999.

Fama, E. F. & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636.

Frazzini, A. & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica*, *57*, 1121–1152.

Graham, B. & Dodd, D. (1934). *Security Analysis*. McGraw-Hill.

Greenwood, R. & Hanson, S. G. (2012). Share issuance and factor timing. *The Journal of Finance*, *67*, 761–798.

Grinblatt, M. & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, *78*(2), 311–339.

Harvey, C. R. (2017). Presidential Address: The Scientific Outlook in Financial Economics. *Duke I&E Research Paper No. 2017-05*.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the Cross-Section of Expected Returns. *The Review of Financial Studies*, *29*(1), 5–68.

Hasbrouck, J. (2009). Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data. *The Journal of Finance*, *64*(3), 1445–1477.

Haugen, R. A. & Heins, J. A. (1975). Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles. *Journal of Financial and Quantitative Analysis*, *10*(5), 775–784.

Henry, E., Lin, S. W., & Yang, Y.-W. (2009). The European-U.S. 'GAAP Gap': IFRS to U.S. GAAP Form 20-F Reconciliations. *Accounting Horizons*, *23*(2), 121–150.

Heston, S., Rouwenhorst, K. G., & Wessels, R. E. (2003). Momentum and Turnover: Evidence from the German Stock Market. *Schmalenbach Business Review*, *55*, 108–135.

Heston, S., Rouwenhorst, K. G., & Wessels, R. E. (1995). The structure of international stock returns and the integration of capital markets. *Journal of Empirical Finance*, *2*(3), 173–197.

Hirshleifer, D. (1988). Residual risk, trading costs, and commodity futures risk premia. *Review of Financial Studies*, *1*, 173–193.

Hirshleifer, D., Hou, K., Teoh, S. H., & Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, *38*, 297–331.

Hirshleifer, D. & Jiang, D. (2010). A financing-based misvaluation factor and the cross-section of expected returns. *Review of Financial Studies*, *23*, 3401–3436.

Horowitz, J. L., Loughran, T., & Savin, N. E. (2000). Three analyses of the firm size premium. *Journal of empirical finance*, *7*, 143–153.

Hou, K., Karolyi, G. A., & Kho, B. C. (2011). What factors drive global stock returns. *Review of Financial Studies*, *24*(8), 2527–2574.

Hou, K., Xue, C., & Lu, Z. (2018). Replicating Anomalies. *Review of Financial Studies (forthcoming).*

Hou, K., Xue, C., & Zhang, L. (2015). Digesting Anomalies: An Investment Approach. *Review of Financial Studies*, *28*(3), 650–705.

Hsu, J., Kalesnik, V., & Viswanathan, V. (2015). A Framework for Assessing Factors and Implementing Smart Beta Strategies. *The Journal of Index Investing*, *6*, 89–97.

Ikenberry, D., Lakonishok, J., & Vermelean. (1995). Market reaction to underreaction to open market share repurchases. *Journal of Financial Economics*, *39*(1), 181–208.

Ince, O. S. & Porter, R. B. (2006). Individual equity return data from Thomson Datastream: Handle with care! *Journal of Financial Research*, *29*(4), 463–479.

Jaganathan, R. & Wang, Z. (1996). The Conditional CAPM and the Cross-Section of Expected Stock Returns. *The Journal of Finance*, *51*(1), 3–53.

Jegadeesh, N. & Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *The Journal of Finance*, *48*, 65–91.

Johann, T. & Theissen, E. (2017). The Best in Town: A Comparative Analysis of Low-Frequency Liquidity Estimators. *Working Paper.*

Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–291.

Korajczyk, R. A. & Sadka, R. (2004). Are momentum profits robust to trading costs? *The Journal of Finance*, *59*(3), 1039–1082.

Korajczyk, R. A. & Sadka, R. (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics*, *87*, 45–72.

Kothari, S. P., Shanken, J., & Sloan, R. (1995). Another look at the cross-section of expected stock returns. *The Journal of Finance*, *50*(1), 185–224.

Kozak, S., Nagel, S., & Santosh, S. (2018). Interpreting factor models. *The Journal of Finance*, *73*(3), 1183–1223.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance*, *49*(5), 1541–1578.

LaPorta, R., Lakonishok, J., Schleifer, A., & Vishny, R. W. (1997). Good news for value stocks: Further evidence on market efficiency. *Journal of Finance*, *52*(2), 859–874.

Leamer, E. E. (1978). *Specification Searches: Ad Hoc Inference with Nonexperimental Data* (1st ed.). Wiley.

Lee, K.-H. (2011). The World Price of Liquidity Risk. *Journal of Financial Economics*, *99*(1), 136–161.

Leippold, M. & Lohre, H. (2012). Data snooping and the global accrual anomaly. *Applied Financial Economics*, *22*(7), 509–535.

Lev, B. & Nissim, D. (2006). The persistence of the accrual anomaly. *Contemporary Accounting Research*, *23*(1), 193–226.

Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, *96*, 175–194.

Lintner, J. (1965). The valuation of risk assets on the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, *47*, 13–37.

Liu, Q., Rhee, S. G., & Zhang, L. (2011). On the Trading Profitability of Penny Stocks. *24th Australasian Finance and Banking Conference 2011 Paper*.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *The Journal of Financial Economics*, *82*, 671–671.

Lo, A. & MacKinlay, C. (1990). Data-snooping biases in tests of financial asset pricing models. *Review of Financial Studies*, *3*, 431–467.

Loughran, T. (1997). Book-To-Market across Firm Size, Exchange, and Seasonality: Is There an Effect? *The Journal of Financial and Quantitative Analysis*, *32*(3), 249–268.

Loughran, T. & Ritter, J. R. (1995). The new issues puzzle. *The Journal of Finance*, *50*, 23–51.

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance*, *7*(1), 77–91.

McKinlay, C. (1995). Multifactor Models do not Explain Deviations from the CAPM. *Journal of Financial Economics*, *38*, 3–28.

McLean, D. R. & Pontiff, J. (2016). Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance*, *71*(1), 5–32.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*, 483–510.

Merton, R. C. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica*, *41*(5), 867–887.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*, 768–783.

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2009). What factors affect the Oslo Stock Exchange? *Norges Bank Working Paper*, (24).

Novy-Marx, R. (2013). The other side of value. *Journal of Financial Economics*, *108*, 1–28.

Novy-Marx, R. & Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *The Review of Financial Studies*, *29*(1), 104–147.

Nygaard, K. (2011). The disposition effect and momentum: Evidence from Norwegian household investors. *Working Paper*.

Ødegaard, B. A. (2018). Empirics of the Oslo Stock Exchange: Basic, descriptive, results 1980-2017. *Working Paper*.

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131.

Pastor, L. & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, *111*, 643–685.

Patton, A. J. & Timmermann, A. (2010). Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts. *Journal of Financial Economics*, *98*, 605–625.

Pincus, M., Rajgopal, S., & Venkatachalam, M. (2007). The accrual anomaly: International evidence. *The Accounting Review*, *82*(1), 169–203.

Plyakha, Y., Uppal, R., & Vilkov, G. (2014). Equal or Value Weighting? Implications for Asset Pricing Tests. *Working Paper*.

Pontiff, J. & Woodgate, A. (2008). Share issuance and cross-sectional returns. *The Journal of Finance*, *63*, 921–945.

Reinganum, M. R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics*, *9*(1), 19–46.

Ritter, J. R. (1991). The long-run performance of initial public offerings, *The Journal of Finance*, *46*, 3–27.

Rosenberg, B., K., R., & Lanstein, R. (1985). Persuasive Evidence of Market Inefficiency. *The Journal of Portfolio Management*, *11*, 9–17.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, *13*, 341–360.

Rouwenhorst, K. G. (1998). International momentum strategies. *Journal of Finance*, *55*, 1217–1269.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *The Journal of Financial Economics*, *80*, 309–349.

Schmidt, P. S., von Arx, U., Schrimpf, A., Wagner, A. F., & Ziegler, A. (2017). On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications. *Swiss Finance Institute Research Paper No. 10-58*.

Shanken, J. (1985). Multivariate tests of the zero-beta CAPM. *Journal of Financial Economics*, *14*, 327–348.

Shanken, J. (1992). On the estimation of beta-pricing models. *Review of Financial Studies*, *5*, 1–33.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*, 425–442.

Shefrin, H. & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance*, *40*(3), 777–790.

Shleifer, A. & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance*, *52*(1), 35–55.

Shumway, T. (1997). The Delisting Bias in CRSP Data. *The Journal of Finance*, *52*(1).

Shumway, T. & Warther, V. A. (1999). The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect. *The Journal of Finance*, *54*(6), 2361–2379.

Skinner, D. J. & Sloan, R. G. (2002). Earnings Surprises, Growth Expectations, and Stock Returns or Don't Let an Earnings Torpedo Sink Your Portfolio. *Review of Accounting Studies*, *7*(2–3), 289–312.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review*, *71*, 289–315.

Stambaugh, R. F. (1997). Analyzing Investments Whose Histories Differ in Length. *NBER Working Paper Series*, (5918).

Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *The Journal of Finance*, *70*, 1903–1948.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *The Journal of Financial Economics*, *104*, 288–302.

Stambaugh, R. F. & Yuan, Y. (2017). Mispricing Factors. *The Review of Financial Studies*, *30*(4), 1270–1315.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A journal of selected papers*, *4*, 25–45.

Stoll, H. R. & Whalley, R. E. (1983). Transaction cost and the small firm effect. *Journal of Financial Economics*, *12*, 57–79.

Titman, S., Wei, J., & Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, *39*, 677–700.

Treynor, J. L. (1961). Market Value, Time, and Risk. *Unpublished Manuscript.*

Treynor, J. L. (1962). Toward a Theory of Market Value of Risky Assets. *Unpublished Manuscript.*

Viale, A., Kolari, J. W., & Fraser, D. R. (2009). Common risk factors in bank stocks. *Journal of Banking and Finance*, *33*(3), 464–472.

Wang, H. & Yu, J. (2013). Dissecting the profitability premium. *Working Paper.*

Ward, J. H. (1963). Hierarchical Grouping to Optimize an Objective Function. *Journal of the American Statistical Association*, *58*(301), 236–244.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica*, *48*, 817–838.

Xing, Y. (2008). Interpreting the Value Effect Through the Q-Theory: An Empirical Investigation. *The Review of Financial Studies*, *21*(4), 1767–1795.

Appendices

A Anomaly Construction

Below I detail the construction of the sorting variables used to construct the one-dimensional anomaly portfolios, the mispricing scores and the factor portfolios. All of the variables are calculated at the end of each month. The sample is restricted to companies non-financial companies listed at the Oslo Stock Exchange, with corporate headquarters in Norway. In an effort to reduce microstructure and illiquidity effects, I require the stocks to: i) have more than 20 trade days in the 12-month period leading up to the end of month $t-1$; ii) have either a 12-month rolling mean turnover above the 2.5 percent level in the cross-section or a 12-month rolling mean bid-ask spread below the 97.5 percent level in the cross-section (as measured by the 2-day corrected spread measure of Abdi and Ranaldo, 2017); and iii) a stock price at the end of month $t-1$ above the 2.5 percent level of the cross-section for the entire sample, to be considered for portfolio selection at the end of month $t-1$.

The variable construction generally follows the methodology laid out in Stambaugh and Yuan (2017) with some discrepancies. Most notably the anomaly portfolios are constructed using OSE quintiles rather than deciles as breakpoints. This is due to the small size of the Norwegian market and to ensure sufficient diversification in each portfolio (see, e.g., Ødegaard, 2018). As opposed to the North-American database, the Compustat Global database does not provide a reporting date for the quarterly items. Thus, when using quarterly items I use those reported for the prior quarter both for earnings and balance sheet information. Nor does the quarterly database provide an item for quarterly net income, hence I have had to create this manually (the construction of which is detailed below). Further note that all companies listed at the Oslo Stock Exchange are required to comply with the IFRS standard, whereas companies listed at the NYSE/AMEX/Nasdaq report according to US GAAP. This leads to a minor difference in the construction of Net Operating Assets as minority interest under IFRS is defined as part of the equity and thus enters positively under operating assets (rather than negatively under liabilities). The last point is, obviously, no more than a technicality. Finally, it is worth noting that net income is typically higher (lower) and shareholder's equity lower (higher) when complying to IFRS (US GAAP), as discussed by among others Henry, Lin, and Yang (2009).

Following Stambaugh and Yuan (2017), when constructing the mispricing factors, I require that a stock have non-missing data for at least three of the anomalies in each cluster to be included in the respective factors cluster. Furthermore, for an anomaly to be included in its mispricing cluster I require that at least 30 stocks have non-missing values for that anomaly.

For the annual data items, the most recent reporting year used is the one that ends at least 4 months before the end of month $t-1$, whereas for return, market capitalization, and index data items I use data for month $t-1$ and earlier. For all of the individual stocks, I require good return data, data on market capitalization, as well as good data on the respective anomaly at the end of month $t-1$ in order to be considered for portfolio selection at the end of month $t-1$. For each stock, I calculate the end of month $t-1$ values of their anomaly rankings as outlined below (Compustat item ID in parenthesis).

The Stambaugh and Yuan anomalies:

1. *Net Stock Issues* are measured as in Fama and French (2008), and calculated as the annual log change in split adjusted shares outstanding (annual item CSHOI times AJEXI). The stocks that have negative net issues get assigned to quantile 1, stocks with zero net issues are assigned to quantile 2, and the rest are assigned to the remaining quantiles.

2. *Composite Equity Issues* is measured as the 12-month cumulative growth in equity market capitalization less the 12-month cumulative stock return. As in Stambaugh and Yuan (2017) it is measured with a 4-month lag to make its timing coincident with net stock issues.

3. *Accruals* is calculated as in Sloan (1996), by subtracting depreciation and amortization costs (annual item DP) from the annual change in noncash working capital, then dividing the quantity by average total assets (annual item AT) for the past two fiscal years. Noncash working capital is defined as the change in current assets (annual item ACT) minus the change in cash and short-term investment (annual item CHE), minus the change in current liabilities (annual item LCT), plus income taxes payable (annual item TXP).

4. *Net Operating Assets* is measured following equations (4), (5), and (6) in Hirshleifer et al. (2004), as operating assets minus operating liabilities, divided by lagged total assets (annual item AT). I measure operating assets as total assets, minus cash and short-term investments (annual item CHE), plus minority interest. Operating liabilities is measured as total assets minus debt included in current liabilities (annual item DLC), minus long-term debt (annual item DLTT), minus common equity (annual item CEQ), minus preferred stock (annual item PSTK). If minority interest and/or preferred stock is missing they are set to zero.

5. *Asset Growth* is defined by Cooper et al. (2008), and measured as the most recent year-on-year annual growth rate of total assets (annual item AT).

6. *Investments-to-Assets* discussed by Titman et al. (2004) andXing (2008) is measured as the changes in gross property, plant, and equipment (annnual item PPEGT), plus the changes in inventory (annual item INVT), divided by lagged total assets (annual item AT).

7. *Distress* is measured using equations (2) and (3) along with Table IV of Campbell et al. (2008), where failure probability is defined as:

$$
\begin{aligned}
CHS = & -20.26NIMTAAVG + 1.42TLMTA - 7.13EXRETAVG + 1.41SIGMA \\
& - 0.045RSIZE - 2.13CASHMTA + 0.075MB - 0.058PRICE - 9.16
\end{aligned}
$$

where,

$$
NIMTAAVG_{t,t-11} = \frac{1-\phi^3}{1-\phi^{12}} \left(NIMTA_{t,t-2} + \cdots + NIMTA_{t-9,t-11}\right)
$$

$$
EXRETAVG_{t,t-11} = \frac{1-\phi}{1-\phi^{12}} \left(EXRET_t + \cdots + \phi^{11} EXRET_{t-11}\right)
$$

$$
SIGMA_{i,t-1,t-2} = \left(252 \times \frac{1}{1-N} \sum_{d \in \{t-1,t-2,t-3\}} r_{i,d}^2\right)^{\frac{1}{2}}
$$

NIMTA is net income divided by firm scale, where firm scale is the sum of total liabilities (quaterly item LTQ) and the market capitalization. As net income is missing in the global database it is calculated as either total revenue (quarterly item REVTQ) minus cost of goods sold (quarterly item COGSQ) minus operating expenses (quarterly item XOPRQ) plus non-operating income (quarterly item NOPIQ) minus income taxes (quarterly item TXTQ), or total revenue minus cost of goods sold minus operating expenses plus interest income (quarterly item IDITQ) minus interest and related expense (quarterly item XINTQ) minus income taxes, or total revenue minus total expenses (quarterly item XTQ), or set to missing, in that order. EXRET is the stocks monthly log return in month s (derived from the daily adjusted price) minus the log return on the Oslo Stock Exchange All Share Index (OSEAX), obtained from Macrobond. If the values for NIMTA and EXRET is missing they are replaced by the cross-sectional means. SIGMA is the stock's the annualized daily (non-centered) standard deviation for the past three months, where at least five non-zero daily returns are required. RSIZE is the log-ratio of the stocks market capitalization to the market capitalization of the OSEAX index. CASHMTA is calculated by dividing cash and short-term investments (quarterly item CHEQ) by firm scale. MB is the market-to-book value, where book equity is increased by ten percent of the difference between market equity and book equity, if the resulting book equity is negative book equity is set to NOK 1. PRICE is the log of the share price truncated above at USD 15 using a floating exchange rate obtained from Norges Bank. All right hand side variables except PRICE are winsorized at the 5 and 95 percent level in the cross-section.

8. *O-score* estimator of bankruptcy probability is defined as in Ohlson (1980):

$$\begin{aligned}O = & -0.407SIZE + 6.03TLTA - 1.43WCTA + 0.076CLCA - 1.72OENEG \\ & - 2.37NITA - 1.83FUTL + 0.285INTWO - 0.521CHIN - 1.32\end{aligned}$$

where,

$$CHIN = \frac{(NI_j - NI_{j-1})}{(|NI_j| + |NI_{j-1}|)}$$

and NI is the net income for year j (annual item NICON).[47] SIZE is the log of total assets (annual item AT); TLTA is the book value of debt (annual item DLC plus annual item DLTT) divided by total assets; WCTA is working capital, defined as current assets minus current liabilities (annual item ACT minus annual item LCT), divided by total assets; CLCA is current liabilities (annual item LCT) divided by current assets; OENEG is a dummy variable which takes the number 1 if total liabilities (LT) exceeds total assets, and zero otherwise; NITA is defined as net income divided by total assets; FUTL is funds from operations (annual item PI) divided by total liabilities; finally INTWO is another dummy variable which takes the number one if net income is negative for the past two years, and zero otherwise.

9. *Momentum* in month $t-1$ is constructed as the $t-12$ to $t-2$ month cumulative stock return, as in Carhart (1997).

10. *Gross Profitability Premium* is calculated as in Novy-Marx (2013) by subtracting the cost of goods sold (annual item COGS) from total revenue (annual item REVT) and dividing the quantity by total assets (annual item AT).

11. *Return on Assets* is measured as in L. Chen et al. (2010) and computed as income before extraordinary items (quarterly item IBQ) divided by lagged total assets (quarterly item ATQ).

[47] Note that the reporting quality for annual net income in the global database is rather poor, thus, for completeness I have derived a similar solution to obtain net income as in the case of the quarterly variable. Specifically, if the annual item NICON is missing, I define net income as either total revenue (annual item REVT) minus cost of goods sold (annual item COGS) minus operating expenses (annual item XOPR) plus non-operating income (annual item NOPI) minus income taxes (annual item TXT), or total revenue minus cost of goods sold minus operating expenses plus interest income (annual item IDIT) minus interest and related expense (annual item XINT) minus income taxes, or earnings before interest (annual item EBIT) plus interest income minus interest and related expense minus income taxes, or total revenue minus total expenses (annual item XT), or set to missing, in that order.

Additional anomalies evaluated:

12. The *beta* anomaly, documentet by among others Black et al. (1972), is measured using a rolling five-year time-series regression based on monthly returns, where I require at least 24 of the past 60 return observations be available. Beta is calculated relative to the one-month return of the OSEAX index, less the 1-month Norwegian Interbank Offered Rate (NIBOR), which proxies for the risk-free rate. Both the index data and the data on NIBOR is obtained from Macrobond.

13. *Size* (market equity) is computed as the (total) number of shares outstanding (daily item CSHOC) times the shareprice (daily item PRCCD). For firms that have several classes of common stock (A- and B-shares), shareprice is the weighted mean of different the different issues and total number of shares outstanding is the total number of shares across all (common) share classes. Companies with negative market equity are excluded. For the construction of the Fama-French factors, SMB and HML, size portfolios for July of year j to June of $j+1$ is measured at the end of June using the June market equity and OSE breakpoints. For all other factors and test assets size is measured at the end of each month $t-1$ using the end of $t-1$ market equity and OSE breakpoints, and rebalanced monthly.

14. *Book-to-Market* is measured following the methodology in Davis, Fama, and French (2000), where the book equity is constructed as the value of shareholder's equity (annual item SEQ), plus (if available) balance sheet deferred taxes and investment tax credit (annual item TXDITC), minus the book value of preferred stock (annual item PSTK). In cases where the book value of preferred stock is missing, I measure it by summing the book value of non-redeemable and redeemable preferred stock (annual items PSTKN and PSTKR). If shareholder's equity is missing, I measure it as the book value of common equity (annual item CEQ) plus the par value of preferred stocks, or the book value of total assets (annual item AT) minus total liabilities (annual item LT) [in that order]. Firms with negative book value are excluded. Portfolios are formed on book-to-market at the end of each June using OSE breakpoints. The book equity used in June of year j is the book equity for the last fiscal year end in $j-1$. Market equity is the market equity at the end of December of $j-1$. The book-to-market portfolios for July of year j to June of $j+1$ include all OSE stocks for which I have market equity data for December of $j-1$ and June of j, and (positive) book equity data for $j-1$.

15. *Liquidity* is proxied by the 2-day adjusted monthly liquidity spread estimator discussed in Abdi and Ranaldo (2017). Following equation (11) in that study it is

defined as,

$$\hat{S}_{two-day} = \frac{1}{N}\sum_{d=1}^{N}\hat{s}_d, \quad \hat{s}_d = \sqrt{max\{4(c_d - \eta_t)(c_d - \eta_{d+1}), 0\}}$$

where c_t is the log closing price on day d, $\eta_d = \ln(H_d)/\ln(L_d)$, where H_d and L_d are the daily high and low prices, N is the number of days in the month, and $\hat{s}_d$ is the two-day estimates.

16. *Idiosyncratic Volatility* (IVOL) is measured following the methodology in Ang et al. (2006), and defined as the standard deviation of the past month's daily benchmark-adjusted returns ($\sqrt{\text{var}(\varepsilon_{i,t})}$), computed as the residuals in the regression,

$$R_{i,d} = \alpha_i + \beta_{i,RMRF}RMRF_d + \beta_{i,SMB}SMB_d + \beta_{i,HML}HML_d + \varepsilon_{i,d}$$

where $R_{i,d}$ is the daily excess return on stock i on day d. The market factor ($RMRF_d$) is proxied by the daily return of the OSEAX index (obtained from Bernt Arne Ødegaard's data library) less the daily risk-free rate, proxied by the (daily) 1-month NIBOR. Finally, SMB_d and HML_d refers to the daily Fama and French (1993) factors (obtained from Bernt Arne Ødegaard's data library).

B Impact on Security Sample when using Alternative Sample Restrictions

Table B.1: Evolution of the securities sample after dynamic filtering in a given year τ (τ = 1996–2017)

Note: This table reports the number of companies left in the sample in a given year τ (τ = 1996–2017) after imposing various dynamic restrictions on the sample, where the second column (*Static*) lists the number of companies left in the sample after the static filtering process described in section 4.1. Columns 3 through 6 show the changes in sample size imposing stricter restrictions than discussed in Section 4.2, where to be considered for portfolio selection at the end of month t a company must: i) have more than 20 trade days in the 12-month period leading up to the end of month t; ii) have either a 12-month rolling mean turnover above the 5 percent level in the cross-section or a 12-month rolling mean bid-ask spread below the 95 percent level in the cross-section (as measured by the 2-day corrected spread measure of Abdi and Ranaldo, 2017); and iii) a stock price at the end of month $t-1$ above the 5 percent level of the cross-section for the entire sample. Columns 3, 7, and 8 show the changes in sample size when imposing the restrictions proposed by Ødegaard (2018), where in addition to the minimum amount of trade days required, a stock must have a share price of more than NOK 10 and a market equity above NOK 1 million in order to be considered for portfolio selection by the end of month t.

			More Restrictive			*Odegaard*	
Year	**Static**	**−Trading**	**−Illiquid**	**−Penny Stocks**	**−Financials**	**−Penny Stocks**	**−Financials**
1996	118	117	68	68	56	92	77
1997	118	118	102	102	85	111	95
1998	136	136	116	116	99	125	109
1999	137	137	122	122	104	120	102
2000	148	147	109	109	94	126	111
2001	172	172	121	119	102	135	112
2002	184	184	140	134	110	121	96
2003	176	176	157	148	114	123	90
2004	164	164	141	137	107	125	95
2005	180	180	146	144	115	146	115
2006	189	189	161	160	128	158	127
2007	199	199	169	169	135	168	132
2008	195	194	176	175	141	155	123
2009	180	180	166	160	127	119	90
2010	179	179	159	154	121	120	89
2011	176	176	160	155	122	123	92
2012	172	172	160	155	122	118	87
2013	173	173	155	151	121	118	90
2014	177	177	151	150	120	131	101
2015	169	169	151	144	114	130	98
2016	170	170	157	153	119	128	96
2017	178	178	157	154	121	137	102
2018	178	178	158	154	117	142	103

C Summary Statistics of Sorting Characteristics

Table C.1: Summary statistics for sorting characteristics: July 1998– June 2018 (240 months)

Notes: This table shows summary statistics for firm characteristics used in the analysis. The CAPM Beta is estimated for each firm relative to the return on the OSEAX index using a rolling 5-year time-series regression based on monthly returns. I require at least 24 of the 60 return observations are available. Size is measured by the market value of equity. Book-to-market (BE/ME) is calculated following the methodology in Davis, Fama, and French (2000). The liquidity spread is proxied by the Abdi and Ranaldo (2017) 2-day corrected spread estimator. Following Ang, Hodrick, Xing, and Zhang (2006), idiosyncratic volatility is define as the standard deviation of the most recent month's daily benchmark-adjusted returns, where the benchmark is the three factors defined by Fama and French (1993). Net Stock Issues at the end of month $t-1$ is calculated as the annual log change in split adjusted shares outstanding, following Fama and French (2008). Accruals is measured as in Sloan (1996) and computed as the annual change in non-cash working capital less depreciation and amortization expense, divided by 2-year average of total assets. Net operation assets is calculated as operating assets minus operating liabilities, divided by lagged total assets, following Hirshleifer, Hou, Teoh, and Zhang (2004). Asset growth in year is calculated as the year-over-year growth rate of total assets as in Cooper, Gulen, and Schill (2008). Investments-to-Assets is defined as the changes in gross property, plant, and equipment plus changes in inventory, divided by lagged total assets, following Titman, Wei, and Xie (2004) and Xing (2008). Distress is calculated on a monthly basis following equations (2) and (3) along with the 12-month column of Table IV in Campbell, Hilscher, and Szilagyi (2008). The O-score is measured as in Ohlson (1980). Following Novy-Marx (2013), the gross profitability premium is calculated as total revenue minus the cost of goods sold, divided by current total assets. Return-on-assets is measured as in L. Chen, Novy-Marx, and Hsieh (2010) and computed as income before extraordinary items divided by the previous quarter's total assets. Composite equity issuance, analyzed by Daniel and Titman (2006) is calculated following the methodology in Stambaugh and Yuan (2017) as the 12-month growth in equity market capitalization less the 12-month cumulative stock return. Finally, the momentum effect of Jegadeesh and Titman (1993) is constructed as in Carhart (1997) and defined as the return from month $t-12$ to $t-2$.

	Mean	**Std.Dev**	**Median**	**25th Percentile**	**75th Percentile**
Beta	0.94	0.65	0.86	0.53	1.31
Size	9155.6	40695.56	1055.63	346.18	4198.25
BE/ME	0.90	2.02	0.64	0.35	1.12
Liquidity Spread (x100)	1.31	1.15	1.08	0.67	1.65
Idiosyncratic Volatility (%)	3.26	2.80	2.51	1.75	3.83
Net Stock Issues	0.13	0.49	0.00	0.00	0.08
Accruals	-0.02	0.63	-0.01	-0.09	0.08
Net Operating Assets	12420.71	52239.37	1398.24	380.54	6470.4
Asset Growth	9.20	401.73	0.07	-0.06	0.24
Investments-to-Assets	0.10	0.76	0.03	0.00	0.11
Distress	4.64	3.33	4.29	2.00	6.92
O-Score	-2.58	29.99	-2.83	-4.32	-1.41
Gross Profitability Premium	0.85	6.68	0.34	0.13	0.70
Return-on-Assets (%)	-0.65	9.45	0.57	-1.40	2.04
Composite Equity Issuance	-12.08	0.34	-12.08	-12.15	-12.04
Momentum (%)	15.20	78.69	3.31	-24.92	35.54

D Industry Portfolios

Table D.1: Monthly Returns and Summary Statistics for *Equal-Weighted* Industry Portfolios

Notes: This table shows the mean monthly returns (in percent) and standard deviations, as well as the skewness, excess kurtosis, worst monthly return and average number of companies within each portfolio, for equal weighted industry portfolios based on the GICS classification in the period from July 1998 through June 2018 (240 months).

Industry	**Return (mean)**	**Std.Dev.**	**Skewness**	**Execess Kurtosis**	**Worst Monthly Performance**	**Average Number of Companies**
10 Energy	0.89	8.25	0.01	0.81	-26.84	26.09
15 Materials	0.39	7.44	-0.03	1.35	-25.75	8.10
20 Industrials	0.95	5.69	-0.59	1.80	-19.87	31.62
25 Cons. Disc.	0.55	7.96	-0.35	1.60	-28.49	10.58
30 Cons. Staples	1.53	8.20	0.22	1.25	-25.19	10.85
35 Health Care	1.46	10.27	1.82	12.80	-31.72	9.42
40 Financials	0.91	4.18	-0.65	3.09	-16.61	30.80
45 IT	0.87	8.78	0.19	1.69	-27.77	24.48
50 Com. Service	1.25	7.43	0.07	3.62	-30.33	4.26
55 Utilities	0.85	8.30	-0.13	2.22	-30.77	3.04
60 Real Estate	1.11	11.02	1.23	5.14	-39.69	3.47

Table D.2: Correlation Between *Equal-Weighted* Industry Portfolios

Notes: This table shows the (Pearson) correlations between equal weighted monthly returns on industry portfolios based on the GICS classification in the perdiod from July 1998 through June 2018 (240 months).

Industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
10 Energy	1.00										
15 Materials	0.61	1.00									
20 Industrials	0.69	0.58	1.00								
25 Cons.Disc	0.58	0.49	0.65	1.00							
30 Cons.Stap	0.52	0.47	0.51	0.45	1.00						
35 Healt.Care	0.34	0.32	0.34	0.39	0.27	1.00					
40 Financials	0.67	0.55	0.68	0.63	0.58	0.45	1.00				
45 IT	0.64	0.49	0.67	0.61	0.45	0.49	0.58	1.00			
50 Com.Service	0.49	0.43	0.50	0.54	0.34	0.37	0.46	0.63	1.00		
55 Utilities	0.28	0.35	0.31	0.27	0.35	0.21	0.34	0.28	0.28	1.00	
60 Real.Estate	0.43	0.44	0.44	0.44	0.31	0.19	0.38	0.42	0.30	0.25	1.00

Table D.3: Monthly Returns and Summary Statistics for *Value-Weighted* Industry Portfolios

Notes: This table shows the mean monthly returns (in percent) and standard deviations, as well as the skewness, excess kurtosis, worst monthly return and average number of companies within each portfolio, for value weighted industry portfolios based on the GICS classification in the period from July 1998 through June 2018 (240 months).

Industry	**Return (mean)**	**Std.Dev.**	**Skewness**	**Execess Kurtosis**	**Worst Monthly Performance**	**Average Number of Companies**
10 Energy	0.84	7.07	-0.49	1.61	-30.60	26.09
15 Materials	1.13	8.06	-0.51	1.89	-36.27	8.10
20 Industrials	0.88	6.05	-0.45	0.73	-17.34	31.62
25 Cons. Disc.	0.39	7.52	-0.50	3.12	-37.13	10.58
30 Cons. Staples	1.28	7.03	-0.67	2.89	-28.79	10.85
35 Health Care	1.36	11.27	1.60	9.51	-34.00	9.42
40 Financials	1.17	6.83	-0.78	3.24	-26.95	30.80
45 IT	0.41	11.64	-0.02	3.03	-40.79	24.48
50 Com. Service	1.26	8.40	-0.17	3.71	-42.37	4.26
55 Utilities	0.89	7.79	-0.34	2.67	-30.77	3.04
60 Real Estate	0.60	9.99	1.46	17.94	-50.24	3.47

Table D.4: Correlation Between *Value-Weighted* Industry Portfolios

Notes: This table shows the (Pearson) correlations between value weighted monthly returns on industry portfolios based on the GICS classification in the perdiod from July 1998 through June 2018 (240 months).

Industry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
10 Energy	1.00										
15 Materials	0.62	1.00									
20 Industrials	0.50	0.49	1.00								
25 Cons.Disc	0.49	0.48	0.51	1.00							
30 Cons.Stap	0.52	0.58	0.53	0.53	1.00						
35 Healt.Care	0.25	0.28	0.31	0.34	0.27	1.00					
40 Financials	0.56	0.61	0.59	0.50	0.63	0.32	1.00				
45 IT	0.47	0.51	0.59	0.57	0.51	0.34	0.50	1.00			
50 Com.Service	0.38	0.47	0.50	0.52	0.42	0.37	0.51	0.62	1.00		
55 Utilities	0.28	0.30	0.31	0.28	0.46	0.18	0.40	0.35	0.31	1.00	
60 Real.Estate	0.34	0.45	0.41	0.46	0.40	0.16	0.52	0.34	0.28	0.35	1.00

E Anomaly Regressions

Table E.1: Anomaly Regressions, July 1998 Through June 2018 (240 months)

Notes: This table report the alphas (left hand side) and accompanying t-statistics (right hand side) for each of the anomalies long leg, short leg, and spread, ordered to produce a positive alpha in the regression,

$$R_{i,t} = \alpha_i + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \varepsilon_{i,t}$$

where $RMRF_t$ and SMB_t are the market and size factors of Fama and French (1993) discussed in Section 3.2.1. The t-statistics are heteroskedasticity consistent based on White (1980). The sample period runs from July 1998 through June 2018 (240 months). The sample period for ROA and Distress starts in October 2004 and July 2005, respectively.

	Alpha			*t-statistic*		
	Long Leg	Short Leg	Spread	Long Leg	Short Leg	Spread
			Panel A: Equal-Weighted Portfolio Returns			
Beta	0.02	0.50	0.48	0.09	2.92	1.49
BM	-0.02	0.48	-0.50	-0.07	2.28	-1.26
NSI	0.63	-0.45	1.15	3.36	-1.66	3.10
Accruals	0.49	0.18	0.31	2.27	0.95	0.97
NOA	0.35	0.26	0.09	1.63	1.56	0.30
Asset Growth	0.14	1.00E-03	0.14	0.57	0.01	0.38
ITA	0.31	-0.18	0.49	1.67	-0.96	1.65
Distress	0.51	0.39	0.12	2.55	1.49	0.35
O-Score	0.71	-0.43	1.14	4.32	-1.85	3.58
GPP	0.45	-0.12	0.57	2.35	-0.45	1.55
ROA	0.80	-0.38	1.18	4.38	-1.41	3.20
CEI	0.66	-0.26	0.92	2.53	-1.21	2.34
MOM	1.54	-0.85	2.39	6.78	-3.10	5.67
Liquidity	-0.32	0.40	-0.72	-1.42	2.28	-2.19
			Panel B: Value-Weighted Portfolio Returns			
Beta	-0.58	0.78	1.36	-1.73	3.51	3.24
BM	-0.30	-0.15	-0.15	-0.79	-0.42	-0.29
NSI	0.28	-0.14	0.45	1.27	-0.34	0.82
Accruals	0.53	-0.05	0.57	1.39	-0.15	1.14
NOA	0.23	0.36	-0.13	0.39	4.42	-0.21
Asset Growth	0.08	-0.41	0.49	0.22	-1.28	1.12
ITA	0.59	-0.15	0.74	2.26	-0.54	1.88

Table E.1 continued from previous page

	Alpha			*t-statistic*		
	Long Leg	Short Leg	Spread	Long Leg	Short Leg	Spread
Distress	0.23	-0.01	0.24	0.75	-0.02	0.54
O-Score	0.45	-1.17	1.62	3.28	-2.86	3.57
GPP	0.40	-0.11	0.51	1.25	-0.41	1.22
ROA	0.54	-0.45	0.99	2.21	-0.93	1.87
CEI	0.15	3.00E-03	0.15	0.38	0.01	0.29
MOM	0.72	-0.99	1.71	2.43	-2.08	2.89
Liquidity	-0.63	0.34	-0.97	-1.44	1.41	-1.75

F Factor and Anomaly Correlations

Table F.1: Correlations Between Equal-Weighted, Quintile-Sorted, Anomaly Spreads

Notes: This table reports the (Pearson) correlations between equal weighted monthly returns of zero investment portfolios on the different CAPM-anomalies for the period between July 1998 and June 2018.

Anomaly	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$RMRF$	1.00																
Beta	-0.68	1.00															
Size	0.04	0.14	1.00														
BM	0.15	-0.11	0.52	1.00													
LIQuidity	0.57	-0.55	0.22	0.16	1.00												
IVOL	-0.35	0.19	-0.48	-0.38	-0.42	1.00											
NSI	-0.36	0.27	-0.04	-0.04	-0.44	0.31	1.00										
Accruals	0.14	-0.12	0.12	0.16	0.00	-0.23	0.00	1.00									
NOA	0.04	0.14	0.41	-0.31	0.24	-0.22	-0.20	-0.03	1.00								
Asset Growth	0.00	0.00	0.39	0.21	0.06	-0.18	0.28	0.48	0.11	1.00							
ITA	0.04	0.00	0.19	-0.03	-0.01	-0.05	0.09	0.31	0.20	0.54	1.00						
Distress	-0.26	0.11	-0.47	-0.47	-0.35	0.35	0.18	0.04	-0.17	-0.13	-0.05	1.00					
O-Score	-0.35	0.15	-0.44	-0.22	-0.34	0.45	0.26	-0.22	-0.26	-0.27	-0.12	0.39	1.00				
GPP	-0.28	0.23	-0.18	-0.26	-0.34	0.26	0.12	0.11	0.05	-0.07	0.00	0.19	0.41	1.00			
ROA	-0.39	0.22	-0.38	-0.34	-0.48	0.51	0.44	-0.11	-0.22	-0.21	-0.14	0.38	0.53	0.50	1.00		
CEI	0.27	-0.31	0.18	0.25	0.32	-0.29	0.05	0.13	0.05	0.14	-0.02	-0.19	-0.17	-0.19	0.01	1.00	
Momentum	-0.34	0.41	-0.42	-0.49	-0.46	0.35	0.26	-0.09	-0.07	-0.17	-0.08	0.40	0.24	0.18	0.41	-0.22	1.00

Table F.2: Correlations Between Value-Weighted, Quintile-Sorted, Anomaly Spreads

Notes: This table reports the (Pearson) correlations between value weighted monthly returns of zero investment portfolios on the different CAPM-anomalies for the period between July 1998 and June 2018.

Anomaly	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$RMRF$	1.00																
Beta	-0.60	1.00															
Size	-0.26	0.08	1.00														
BM	-0.01	-0.02	0.14	1.00													
LIQuidity	0.27	-0.43	0.11	0.07	1.00												
IVOL	-0.14	0.28	-0.19	-0.14	-0.42	1.00											
NSI	-0.21	0.27	0.03	-0.02	-0.29	0.32	1.00										
Accruals	0.24	-0.12	-0.17	-0.05	0.06	-0.03	-0.06	1.00									
NOA	0.12	-0.22	0.19	-0.24	0.44	-0.35	-0.24	0.34	1.00								
Asset Growth	-0.17	0.12	0.16	0.18	-0.04	0.05	0.15	0.15	-0.06	1.00							
ITA	-0.12	0.13	0.15	0.03	-0.06	0.07	0.11	0.03	0.11	0.50	1.00						
Distress	-0.12	0.14	-0.07	-0.41	-0.24	0.16	0.05	0.05	-0.06	-0.18	-0.19	1.00					
O-Score	-0.22	0.23	-0.30	0.00	-0.32	0.31	0.30	-0.29	-0.58	-0.16	-0.14	0.17	1.00				
GPP	0.02	-0.19	0.11	-0.31	0.11	0.05	-0.06	0.08	0.18	0.00	0.02	-0.02	-0.02	1.00			
ROA	-0.04	0.16	-0.16	-0.36	-0.32	0.27	0.10	-0.02	-0.19	-0.10	-0.03	0.16	0.30	0.17	1.00		
CEI	0.26	-0.30	0.04	-0.09	0.30	-0.17	0.15	0.31	0.38	-0.04	-0.11	-0.02	-0.28	0.05	-0.05	1.00	
Momentum	-0.13	0.35	-0.11	-0.38	-0.32	0.27	0.05	0.13	-0.02	0.05	0.07	0.40	0.02	-0.01	0.36	-0.07	1.00

Table F.3: Factor Correlations

Notes: This table reports the (Pearson) correlations between the monthly returns of the value weighted market, SMB, SMB_{CM}, SMB_M, HML, UMO, $MGMT$, $PERF$, $MNOR$, and the LIQ factors for the period between July 1998 and June 2018.

Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$RMRF$	1.00									
SMB	-0.37	1.00								
SMB (M-3)	-0.22	0.71	1.00							
SMB (M-4)	-0.28	0.76	0.85	1.00						
HML	-0.13	0.01	-0.03	0.06	1.00					
UMO	-0.16	0.04	-0.04	-0.03	-0.09	1.00				
$MGMT$	0.13	0.15	0.32	0.23	-0.13	0.39	1.00			
$PERF$	-0.32	-0.13	-0.27	-0.22	0.07	0.40	-0.03	1.00		
$MNOR$	-0.21	0.00	-0.05	-0.04	-0.18	0.51	0.13	0.42	1.00	
LIQ	0.30	0.12	0.25	0.16	-0.21	0.09	0.35	-0.44	0.02	1.00

Table F.4: Factor Rank Correlations

Notes: This table reports the (Kendall) rank correlations between the monthly returns of the value weighted market, SMB, SMB_{CM}, SMB_M, HML, UMO, $MGMT$, $PERF$, $MNOR$, and the LIQ factors for the period between July 1998 and June 2018.

Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$RMRF$	1.00									
SMB	-0.22	1.00								
SMB_{CM}	-0.15	0.48	1.00							
SMB_M	-0.20	0.57	0.63	1.00						
HML	-0.07	0.02	-0.01	0.06	1.00					
UMO	-0.13	0.04	-0.01	-0.02	-0.08	1.00				
$MGMT$	0.08	0.16	0.23	0.15	-0.11	0.26	1.00			
$PERF$	-0.23	-0.11	-0.20	-0.16	0.02	0.26	-0.07	1.00		
$MNOR$	-0.11	0.01	-0.04	-0.04	-0.11	0.33	0.07	0.25	1.00	
LIQ	0.17	0.14	0.20	0.16	-0.13	-0.01	0.20	-0.33	0.03	1.00

G Normality of the Factors

Table G.1: Non-Normality of Monthly Factor Returns, OSE: July 1998 – June 2018

Notes: This table shows the mean annualized returns and standard deviations, as well as, skewness, excess kurtosis, and the best and worst monthly returns of the researched factors. The anomaly factors (Beta:Momentum) are value weighted, zero investment portfolios based on OSE-quintiles (long 1, short 5), sorted such that a high quintile is associated with a low future return in the literature. All factors are scaled to 10 percent (annualized) volatility. The portfolios of factors are equally weighted averages of the factors included in the respective models and also scaled to 10 percent volatility.

Factor	**Mean Annualized Return**	**Skewness**	**Excess Kurtosis**	**Worst Monthly Return**	**Best Monthly Return**
$RMRF$	3.84	-0.86	2.54	-11.61	7.17
$RMRF_{EW}$	3.30	-0.61	1.60	-10.83	7.92
Beta	4.04	0.12	1.47	-9.35	9.57
Size	-3.24	0.01	0.51	-10.18	8.28
BM	-0.28	-0.24	0.58	-9.81	7.84
Liquidity	-1.77	1.14	5.21	-8.99	15.80
IVOL	6.55	-0.06	2.08	-12.35	10.75
NSI	0.76	0.08	1.21	-9.65	11.96
Accruals	3.57	3.64	34.43	-8.74	28.02
NOA	1.46	2.40	17.21	-8.02	23.03
Asset Growth	2.90	0.05	0.89	-10.01	8.43
ITA	4.86	0.02	0.53	-9.36	8.92
Distress	0.10	-0.10	-0.13	-7.18	7.15
O-Score	3.97	-0.40	2.96	-14.74	10.91
GPP	3.61	0.29	0.90	-7.09	10.39
ROA	3.24	0.26	1.79	-7.91	11.46
CEI	1.62	0.44	2.34	-11.12	13.13
Momentum	5.19	-0.14	0.72	-8.19	8.16
SMB	2.95	0.06	1.79	-11.17	11.41
SMB_{CM}	1.05	0.53	1.48	-9.17	9.98
SMB_M	-0.30	0.13	0.77	-9.76	9.65

Table G.1 continued from previous page

Factor	**Mean Annualized Return**	**Skewness**	**Excess Kurtosis**	**Worst Monthly Return**	**Best Monthly Return**
HML	2.35	0.11	1.68	-10.58	12.39
UMO	8.29	0.06	0.49	-6.53	9.47
$MGMT$	4.92	-0.73	19.28	-21.67	18.53
$PERF$	4.76	-0.19	1.20	-9.10	9.18
$MNOR$	10.47	0.08	0.76	-7.46	10.46
LIQ	-3.16	0.30	1.34	-8.37	10.65
FF-3 Portfolio	6.52	0.17	0.28	-8.36	9.25
M-3 Portfolio	9.05	0.60	2.12	-8.39	13.19
M-4 Portfolio	7.71	-0.83	10.46	-19.39	14.18
NOR Portfolio	13.01	0.42	0.49	-6.92	10.95
NSO Portfolio	1.99	0.15	0.69	-7.87	9.69

H Performance Plots

H.1 Rolling 12-Month Correlations – Model Factors Relative to the Market Factor

Figure H.1: Correlations for the FF-3 Factors

Notes: This figure shows the 12-month rolling correlation between the SMB and HML factors of Fama and French (1993) relative to the value-weighted market factor, $RMRF$.

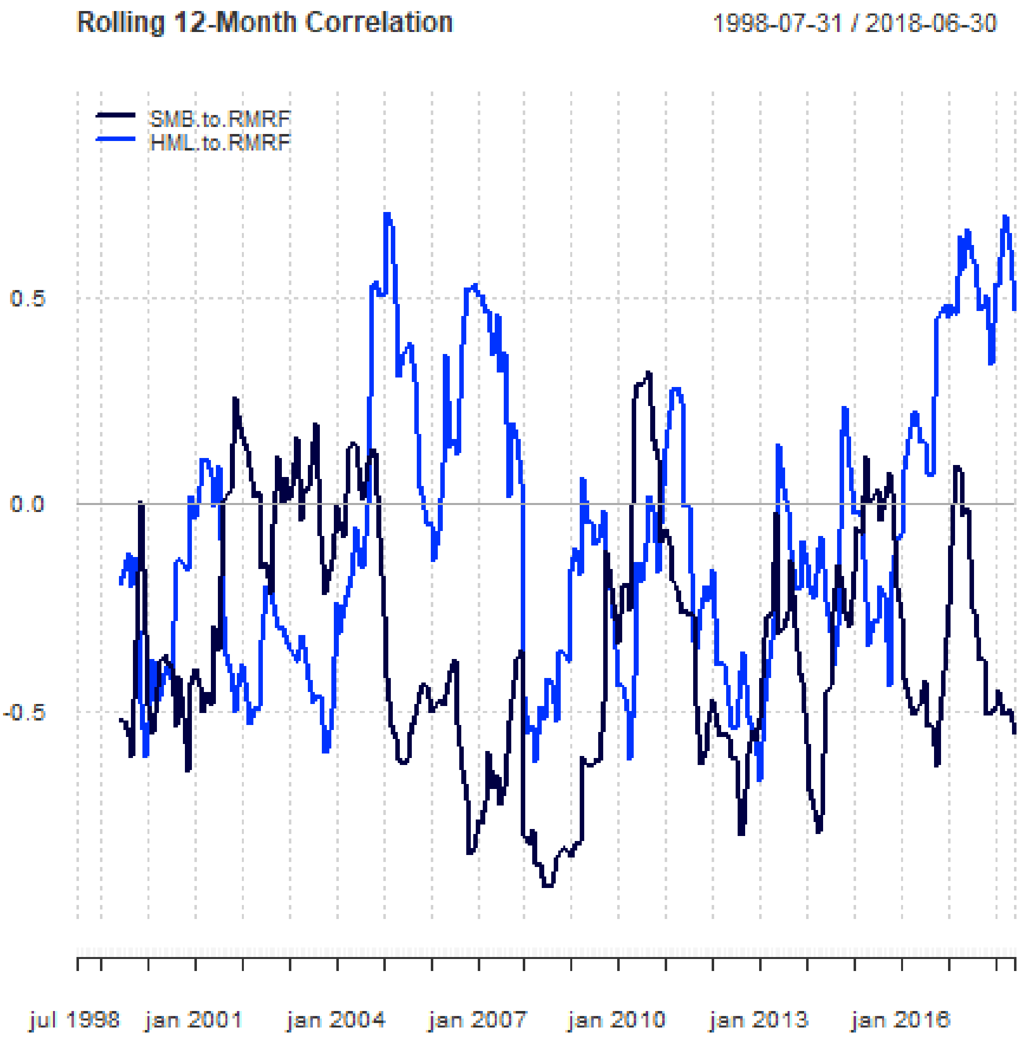


Figure H.2: Correlations for the M-3 Factors

Notes: This figure shows the 12-month rolling correlation between the SMB_{CM} and UMO factors of Stambaugh and Yuan (2017) relative to the value-weighted market factor, $RMRF$.

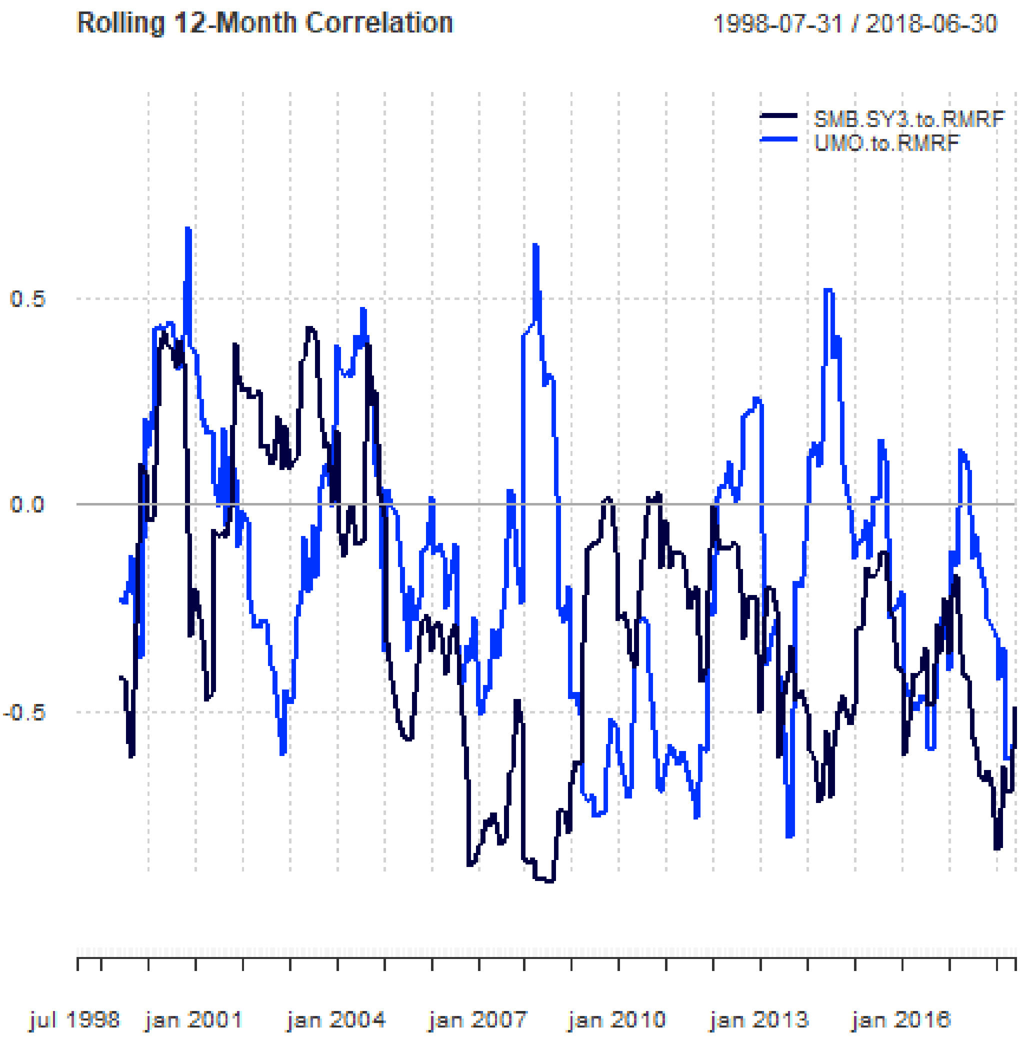


Figure H.3: Correlations for the M-4 Factors

Notes: This figure shows the 12-month rolling correlation between the SMB_M, $MGMT$, and $PERF$ factors of Stambaugh and Yuan (2017) relative to the value-weighted market factor, $RMRF$.

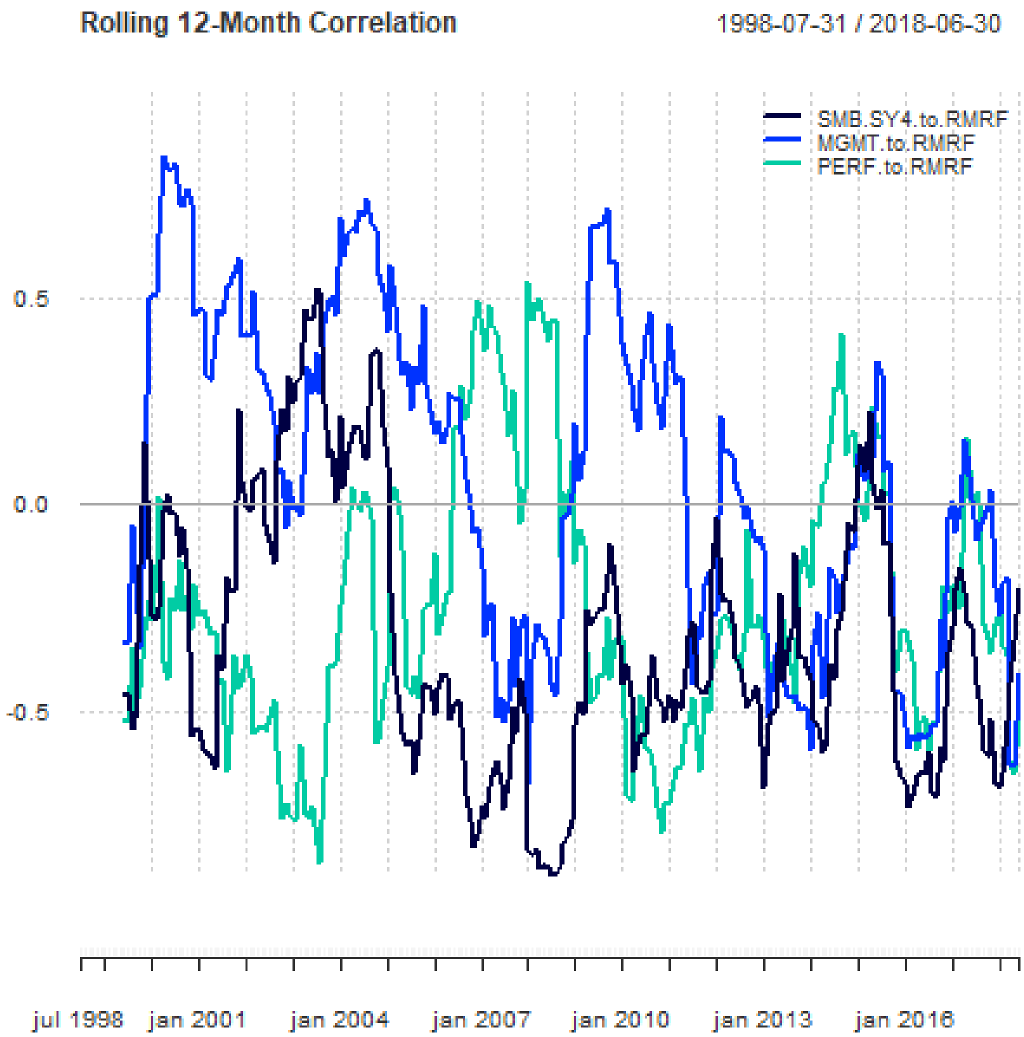


Figure H.4: Correlations for the NOR Factors

Notes: This figure shows the 12-month rolling correlation between the SMB-factor of Fama and French (1993) and the $MNOR$-factor relative to the value-weighted market factor, $RMRF$.

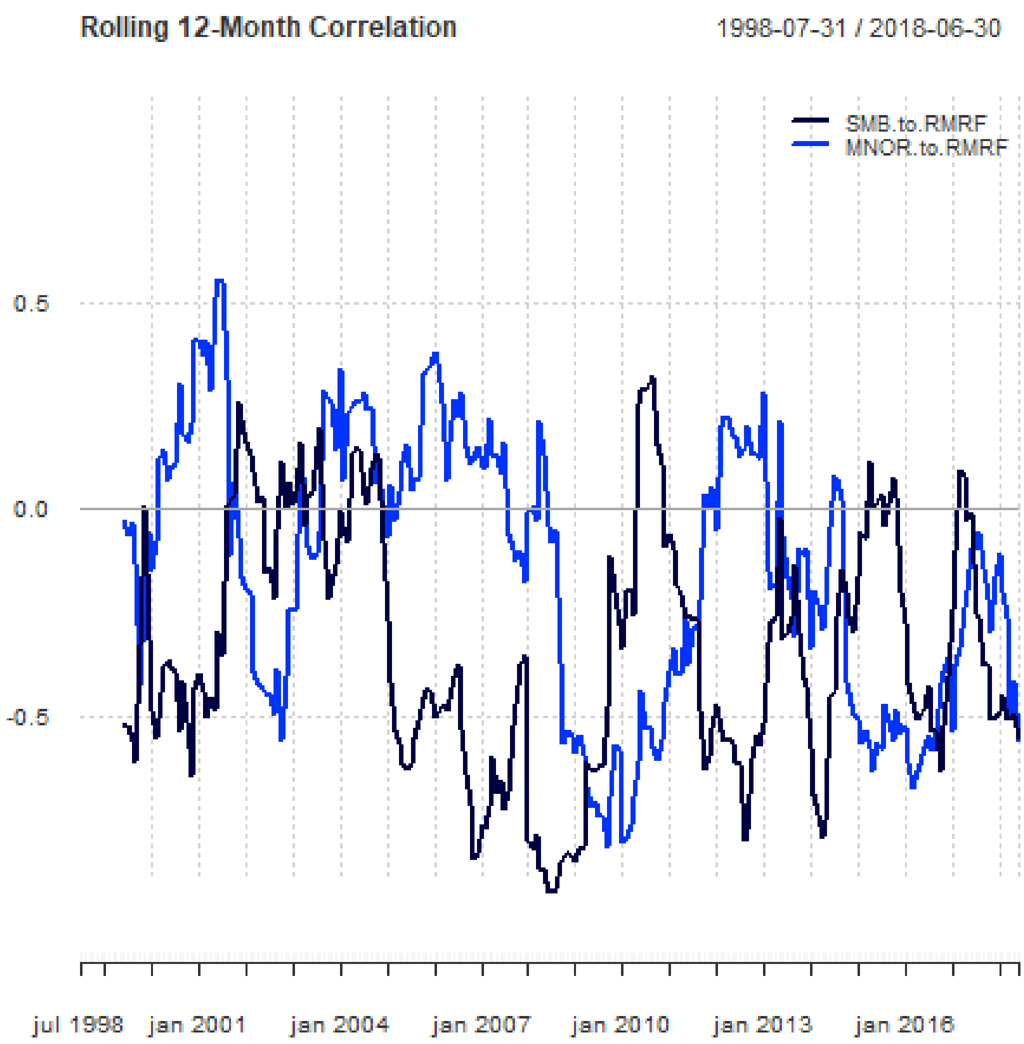
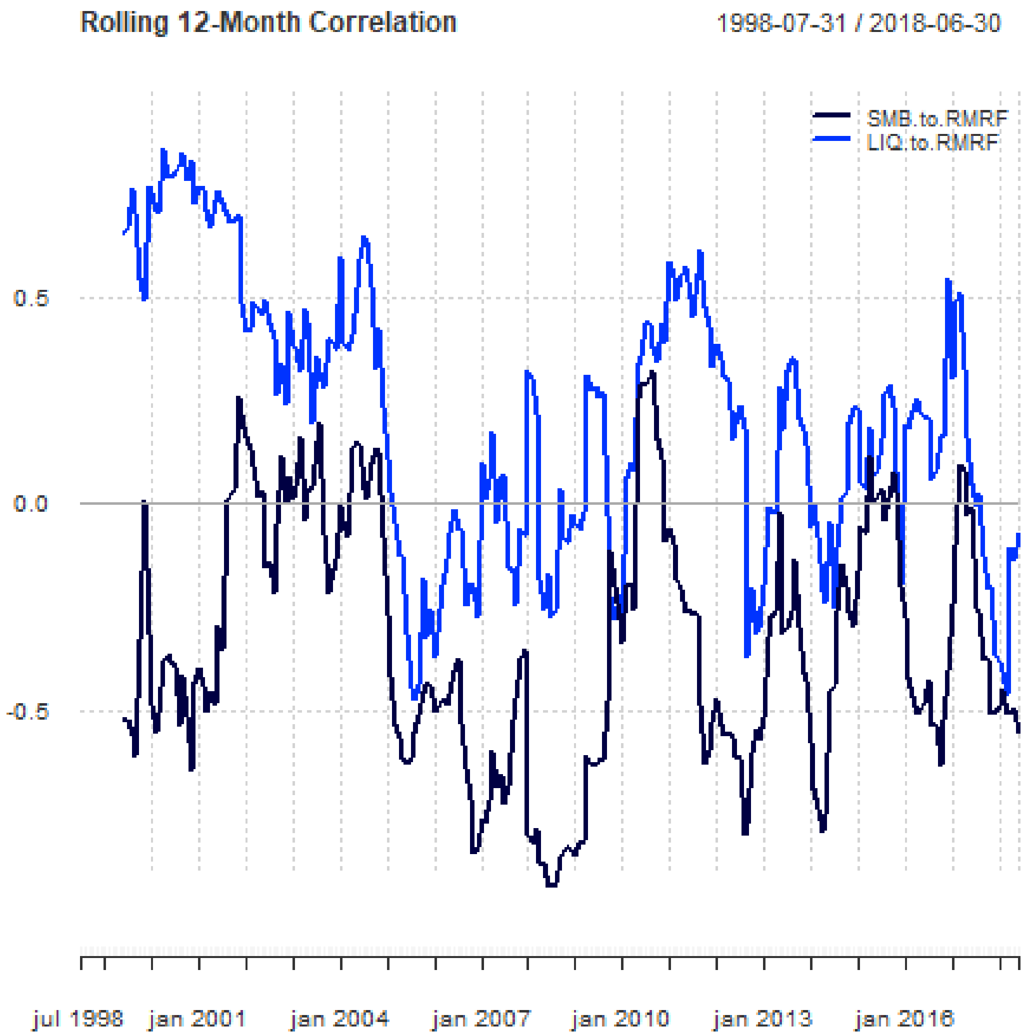


Figure H.5: Correlations for the NSO Factors

Notes: This figure shows the 12-month rolling correlation between the SMB-factor of Fama and French (1993) and the LIQ-factor of Næs, Skjeltorp, and Ødegaard (2009), proxied by the Abdi and Ranaldo (2017) liquidity spread estimator, relative to the value-weighted market factor, $RMRF$.



H.2 Performance Summary – Factor Portfolios

Figure H.6: FF-3 Portfolio Performance Breakdown

Notes: This figure shows the cumulative return (top) and the drawdowns from peak equity (bottom) for the factors in the FF-3 model, as well as an equally invested portfolio of those factors and that portfolios monthly return (middle). The black line shows the performance of the FF-3 factor portfolio, equally invested in the market factor, as well as the SMB and HML factors of Fama and French (1993); the blue line shows the value-weighted return on the market in excess of the 1-month NIBOR, $RMRF$; the green line shows the return on the SMB-factor; the yellow line shows the return on the HML-factor. All factors are scaled to 10 percent (annual) volatility. The FF-3 portfolio is also scaled to 10 percent (annual) volatility.

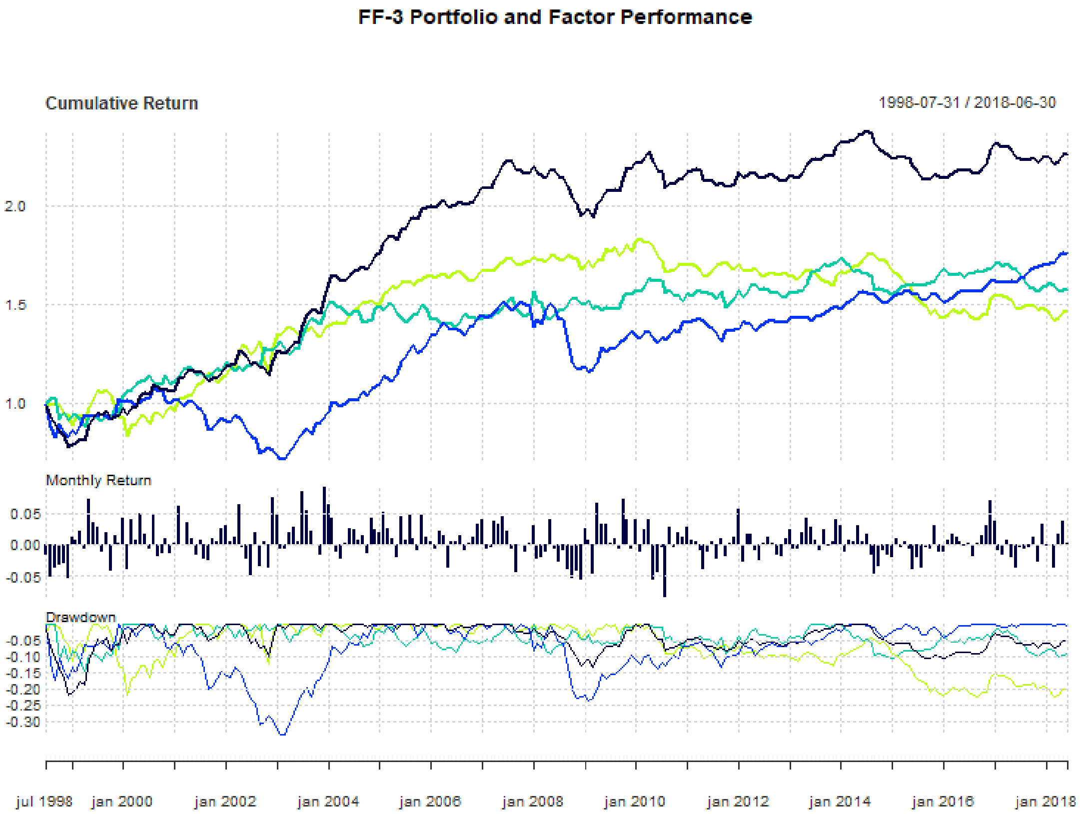


Figure H.7: M-3 Portfolio Performance Breakdown

Notes: This figure shows the cumulative return (top) and the drawdowns from peak equity (bottom) for the factors in the M-3 model, as well as an equally invested portfolio of those factors and that portfolios monthly return (middle). The black line shows the performance of the M-4 factor portfolio, equally invested in the market factor, as well as the SMB_{CM} and UMO factors of Stambaugh and Yuan (2017); the blue line shows the value-weighted return on the market in excess of the 1-month NIBOR, $RMRF$; the green line shows the return on the SMB_{CM}-factor; the yellow line shows the return on the UMO-factor. All factors are scaled to 10 percent (annual) volatility. The M-3 portfolio is also scaled to 10 percent (annual) volatility

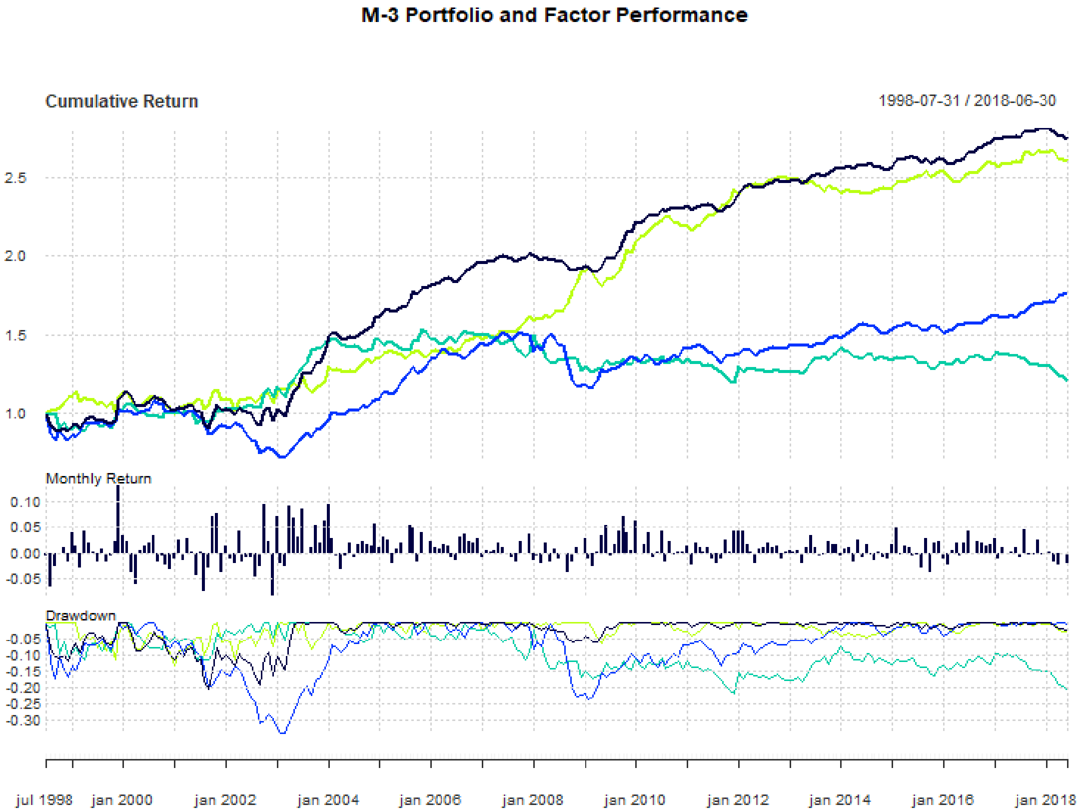


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Figure H.8: M-4 Portfolio Performance Breakdown

Notes: This figure shows the cumulative return (top) and the drawdowns from peak equity (bottom) for the factors in the M-4 model, as well as an equally invested portfolio of those factors and that portfolios monthly return (middle). The black line shows the performance of the M-4 factor portfolio, equally invested in the market factor, as well as the SMB, $MGMT$, and $PERF$ factors of Stambaugh and Yuan (2017); the blue line shows the value-weighted return on the market in excess of the 1-month NIBOR, $RMRF$; the green line shows the return on the SMB_M-factor; the yellow line shows the return on the $MGMT-factor$; the orange line shows the return on the $PERF$-factor. All factors are scaled to 10 percent (annual) volatility. The M-4 portfolio is also scaled to 10 percent (annual) volatility.

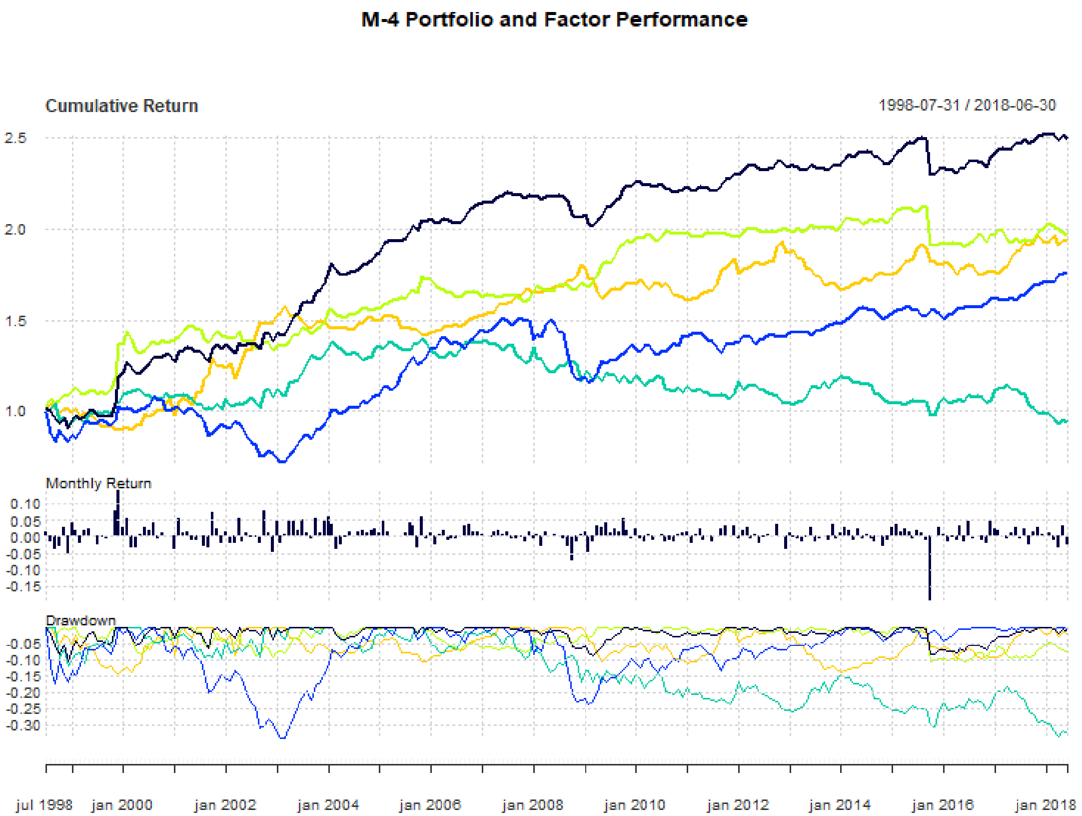


Figure H.9: NOR Portfolio Performance Breakdown

Notes: This figure shows the cumulative return (top) and the drawdowns from peak equity (bottom) for the factors in the NOR model, as well as an equally invested portfolio of those factors and that portfolios monthly return (middle). The black line shows the performance of the NOR factor portfolio, equally invested in the market factor, as well as the SMB-factor of Fama and French (1993) and the $MNOR$-factor; the blue line shows the value-weighted return on the market in excess of the 1-month NIBOR, $RMRF$; the green line shows the return on the SMB-factor; the yellow line shows the return on the $MNOR$-factor. All factors are scaled to 10 percent (annual) volatility. The NOR portfolio is also scaled to 10 percent (annual) volatility.

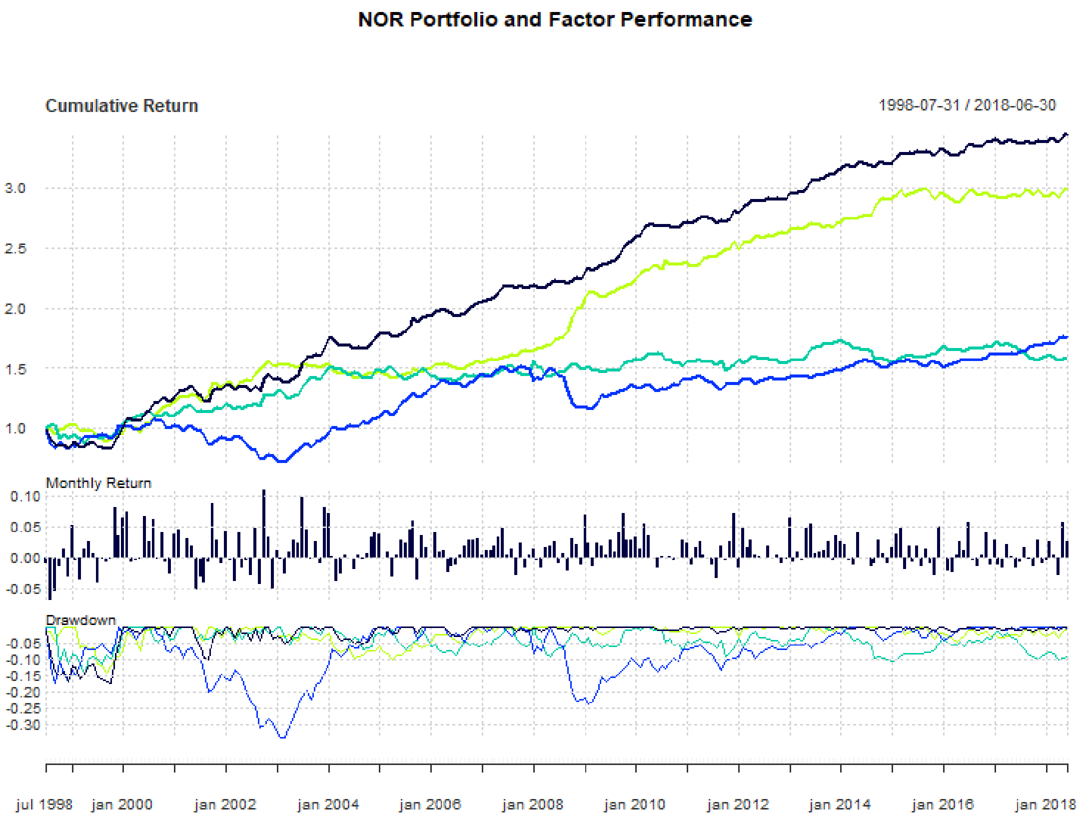


Figure H.10: NSO Portfolio Performance Breakdown

Notes: This figure shows the cumulative return (top) and the drawdowns from peak equity (bottom) for the factors in the NSO model, as well as an equally invested portfolio of those factors and that portfolios monthly return (middle). The black line shows the performance of the NSO factor portfolio, equally invested in the market factor, as well as the SMB-factor of Fama and French (1993) and the LIQ-factor of Næs, Skjeltorp, and Ødegaard (2009) (proxied by the Abdi and Ranaldo (2017) liquidity spread estimator); the blue line shows the value-weighted return on the market in excess of the 1-month NIBOR, $RMRF$; the green line shows the return on the SMB-factor; the yellow line shows the return on the LIQ-factor. All factors are scaled to 10 percent (annual) volatility. The NSO portfolio is also scaled to 10 percent (annual) volatility.

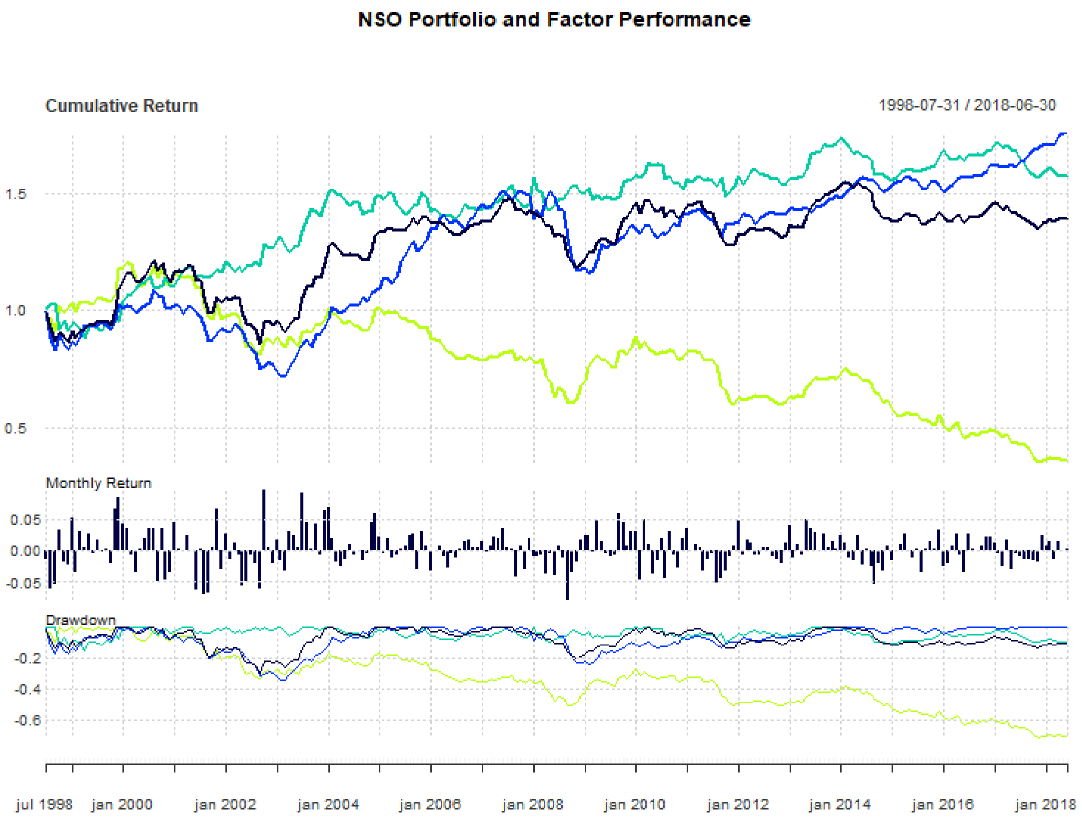
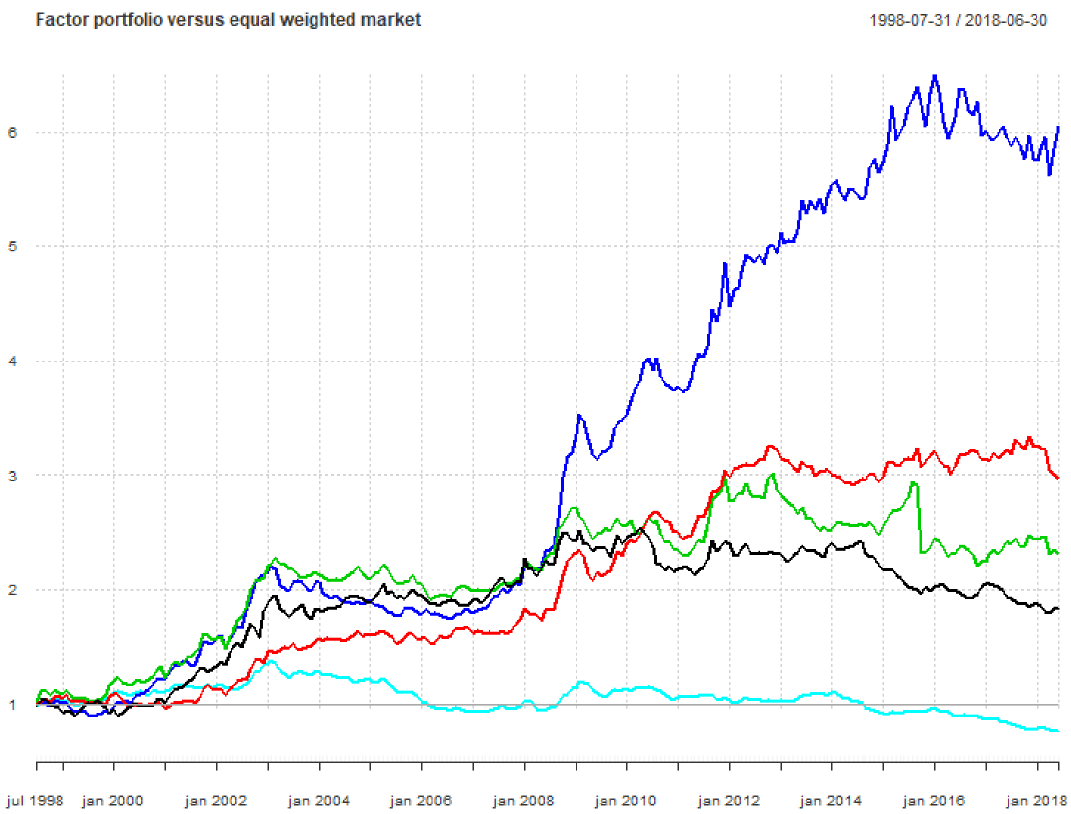


Figure H.11: Factor Portfolios Performance Relative to an Equal Weighted Benchmark

Notes: This figure shows the cumulative over-/under-performance of the five equal weighted factor portfolios relative to an equal weighted market index, $RMRF_{EW}$. The black line shows the return on the FF-3 portfolio (invested in $RMRF$, SMB, and HML); the red line shows the return on the M-3 portfolio (invested in $RMRF$, SMB_{CM}, and UMO; the green line shows the return on the M-4 portfolio invested in $RMRF$, SMB_M, $MGMT$, and $PERF$); the blue line shows the return on the NOR portfolio (invested in $RMRF$, SMB, and $MNOR$); and the turquoise line shows the return on the NSO portfolio (invested in $RMRF$, SMB, and LIQ). Both the benchmark portfolio and the factor portfolios are scaled to 10 percent annualized volatility.



I GRS-Test Performed on Various Test Assets

Table I.1: Abilities of Models CAPM, FF-3, M-3, M-4, NOR, and NSO to Accommodate Different Groups of Test Assets, From July 1998 Through June 2018 (240 months)

Notes: This table reports measures that summarizes to which degree different groups of test assets produce alpha under five different factor models: the CAPM of Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966), denoted CAPM; the three-factor model of Fama and French (1993), denoted FF-3;the three-factor mispricing model of Stambaugh and Yuan (2017), denoted M-3; the four-factor mispricing model of Stambaugh and Yuan (2017), denoted M-4; the three-factor Norwegian mispricing model, denoted NOR; and the three-factor model of Næs, Skjeltorp, and Ødegaard (2009), denoted NSO. For each model and test asset group, the table reports the average absolute alpha $A|\alpha_i|$, the F-statistic and associated p-value for the GRS-test of Gibbons, Ross, and Shanken (1989), and the average adjusted R-squared, A(adj. R^2). The right-hand side of the table reports these summary statistics for value weighted test assets versus a value weighted market factor, while the left-hand side of reports the statistics for equally weighted test assets versus an equal weighted market factor. Panel A reports data for industry portfolios based on the GICS-classification for the full sample period. The following industries are excluded due to there being to few companies in the sample: Health Care; Communication Services; Utilities; and Real Estate. Panels B through F reports full sample summary statistics for independent 3 x 3 sorted portfolios on size and book-to-market; size and the composite mispricing measure (P) of Stambaugh and Yuan, 2017; size and the Norwegian composite mispricing measure (PA); size and liquidity; and PX and idiosyncratic volatility as defined by Ang, Hodrick, Xing, and Zhang (2006).

	Value-Weighted				*Equal-Weighted*			
	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)
Panel A: 7 Industry Portfolios, OSE, July 1998 – June 2018								
CAPM	0.34	1.02	0.42	0.55	0.31	1.30	0.25	0.61
FF-3	0.36	1.40	0.21	0.58	0.29	1.30	0.25	0.64
M-3	0.47	1.93	0.07	0.59	0.33	1.61	0.13	0.63
M-4	0.35	0.95	0.47	0.58	0.29	1.11	0.36	0.63
NOR	0.56	2.10	0.04	0.57	0.36	1.66	0.12	0.63
NSO	0.31	0.91	0.50	0.59	0.30	1.27	0.27	0.63
Panel B: 9 Portfolios Formed on Size / BM, OSE, July 1998 – June 2018								
CAPM	0.11	0.91	0.52	0.52	0.14	1.03	0.41	0.61
FF-3	0.43	1.20	0.29	0.62	0.22	1.39	0.19	0.67
M-3	0.24	1.84	0.06	0.63	0.12	1.64	0.10	0.65

Table I.1 continued from previous page

	Value-Weighted				*Equal-Weighted*			
	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)
M-4	0.17	1.47	0.16	0.64	0.17	1.66	0.10	0.67
NOR	0.32	2.53	0.01	0.61	0.23	2.93	2.65E-03	0.66
NSO	0.28	1.01	0.43	0.62	0.21	1.52	0.14	0.65
Panel C: 9 Portfolios Formed on Size / P, OSE, July 1998 – June 2018								
CAPM	0.51	2.38	0.01	0.52	0.53	2.28	0.02	0.61
FF-3	0.60	2.94	2.51E-03	0.62	0.56	2.80	3.85E-03	0.66
M-3	0.33	1.94	0.05	0.66	0.28	1.28	0.25	0.68
M-4	0.38	1.73	0.08	0.66	0.37	1.53	0.14	0.68
NOR	0.46	1.91	0.05	0.62	0.37	1.86	0.06	0.66
NSO	0.62	2.55	0.01	0.63	0.61	2.83	3.54E-03	0.66
Panel D: 9 Portfolios Formed on Size / PA, OSE, July 1998 – June 2018								
CAPM	0.43	2.26	0.02	0.52	0.41	2.22	0.02	0.61
FF-3	0.46	2.87	3.13E-03	0.61	0.43	3.07	1.72E-03	0.66
M-3	0.25	1.39	0.19	0.64	0.26	1.34	0.22	0.66
M-4	0.35	1.42	0.18	0.64	0.32	1.35	0.21	0.66
NOR	0.29	0.78	0.64	0.63	0.16	0.90	0.53	0.67
NSO	0.46	2.53	0.01	0.62	0.43	2.82	3.68E-03	0.66
Panel E: 9 Portfolios Formed on Size / LIQ, OSE, July 1998 – June 2018								
CAPM	0.29	1.26	0.26	0.51	0.32	1.29	0.24	0.59
FF-3	0.40	1.42	0.18	0.59	0.32	1.57	0.13	0.63
M-3	0.38	1.40	0.19	0.61	0.36	1.56	0.13	0.63
M-4	0.25	1.05	0.40	0.63	0.26	1.01	0.43	0.64
NOR	0.50	2.16	0.03	0.59	0.47	2.42	0.01	0.63
NSO	0.34	1.06	0.40	0.63	0.31	1.05	0.40	0.66
Panel F: 9 Portfolios Formed on PA / IVOL, OSE, July 1998 – June 2018								
CAPM	1.74	0.08	0.26	0.50	2.10	0.03	0.34	0.50
FF-3	2.35	0.02	0.30	0.52	2.77	0.00	0.42	0.55
M-3	2.02	0.04	0.41	0.55	2.24	0.02	0.44	0.56
M-4	1.25	0.27	0.29	0.56	1.41	0.19	0.31	0.57

Table I.1 continued from previous page

	Value-Weighted				*Equal-Weighted*			
	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)	$A\|\alpha_i\|$	F-stat	p-value	A(adj. R^2)
NOR	1.23	0.28	0.44	0.54	1.70	0.09	0.47	0.56
NSO	1.71	0.09	0.25	0.55	2.07	0.03	0.43	0.55

J Factor Loadings on Different Test Assets

J.1 Factor Loadings for Value-Weighted Anomaly Portfolios

Table J.1: The Fama-French 3-factor model for OSE – Anomaly Portfolios

Notes: This table reports the estimation results of the 3-factor model discussed in Fama and French (1993) for OSE. The model is estimated with long-short anomaly portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR..

Portfolio	α	β_{RMRF}	β_{SMB}	β_{HML}	t_{α}	t_{RMRF}	t_{SMB}	t_{HML}
Beta	1.26	-0.75	0.10	0.22	3.07	-8.24	0.79	2.66
Size	1.58	-0.55	-1.00	0.09	3.45	-5.93	-8.17	0.96
BM	0.65	0.05	0.24	-0.31	1.58	0.56	2.02	-4.93
NSI	0.71	-0.12	-0.33	-0.14	1.93	-1.78	-2.60	-1.99
Accruals	0.20	0.33	-0.01	-0.12	0.40	2.50	-0.10	-1.15
NOA	1.63	-0.28	-0.34	0.17	2.77	-2.42	-1.93	1.38
Asset Growth	-0.88	0.51	0.48	-0.20	-1.60	4.49	2.63	-1.63
ITA	-0.85	-0.06	0.80	0.10	-2.67	-1.16	9.30	1.01
Distress	-0.52	0.13	0.26	0.80	-1.14	1.32	1.91	9.34
O-score	0.38	-0.31	-0.18	0.15	0.71	-2.24	-1.19	1.40
GPP	0.56	0.37	0.12	0.03	1.08	2.44	0.95	0.23
ROA	0.16	0.37	0.87	-0.64	0.27	2.20	6.75	-4.14
CEI	0.44	-0.08	0.45	0.11	1.00	-0.89	3.37	1.10
Momentum	0.76	-0.03	0.46	-0.05	1.93	-0.35	3.65	-0.71
Liquidity	0.18	-0.12	-0.18	-0.10	0.62	-2.76	-2.65	-2.11

Table J.2: A Composite Mispricing-model for OSE – Anomaly Portfolios

Notes: This table reports the estimation results of the Stambaugh and Yuan (2017) M-3 model for OSE from July 1998 through June 2018 (240 months). The model is estimated with long-short anomaly portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \beta_{i,3} UMO_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{UMO}	t_α	t_{RMRF}	t_{SMB}	t_{UMO}
Beta	1.45	-0.83	-0.15	0.00	3.44	-8.99	-1.57	-0.01
Size	1.66	-0.51	-0.88	-0.19	3.90	-5.28	-9.44	-1.95
BM	0.64	0.05	0.16	-0.03	1.48	0.61	1.82	-0.47
NSI	0.30	-0.05	-0.25	0.17	0.86	-0.85	-3.05	2.36
Accruals	-0.49	0.46	0.27	0.36	-1.02	3.47	2.60	3.75
NOA	0.89	-0.20	-0.37	0.48	1.50	-1.89	-2.66	4.16
Asset Growth	-0.90	0.50	0.46	0.03	-1.58	4.53	3.82	0.28
ITA	-0.62	-0.13	0.74	0.01	-2.03	-2.17	10.47	0.13
Distress	0.32	-0.04	0.13	-0.26	0.60	-0.37	1.06	-2.92
O-score	0.30	-0.30	-0.15	0.06	0.57	-2.14	-1.22	0.66
GPP	0.11	0.40	0.04	0.33	0.23	2.07	0.26	1.76
ROA	-0.77	0.51	1.02	0.52	-1.34	2.65	7.68	2.75
CEI	0.50	-0.17	0.08	0.12	1.07	-1.55	0.73	1.15
Momentum	0.68	-0.06	0.30	0.13	1.65	-0.76	3.05	1.95
Liquidity	-0.08	-0.06	-0.07	0.10	-0.29	-1.61	-1.26	2.46

Table J.3: A 4-factor mispricing model for OSE – Anomaly Portfolios

Notes: This table reports the estimation results of the Stambaugh and Yuan (2017) M-4 model for OSE from July 1998 through June 2018 (240 months). The model is estimated with long-short anomaly portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1}RMRF_t + \beta_{i,2}SMB_t + \beta_{i,3}MGMT_t + +\beta_{i,4}PERF_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{MGMT}	β_{PERF}	t_α	t_{RMRF}	t_{SMB}	t_{MGMT}	t_{PERF}
Beta	1.10	-0.62	0.19	-0.08	0.26	2.80	-6.32	1.78	-1.56	4.55
Size	1.19	-0.25	-0.54	-0.34	0.26	2.81	-3.31	-5.26	-3.44	3.70
BM	0.74	0.02	0.13	0.00	-0.08	1.69	0.15	1.07	-0.08	-1.28
NSI	0.30	0.09	-0.03	-0.11	0.23	0.80	1.24	-0.25	-2.47	4.00
Accruals	-0.20	0.26	-0.08	0.34	0.00	-0.40	1.99	-0.67	3.72	-0.06
NOA	0.69	0.04	-0.03	0.04	0.59	1.19	0.33	-0.23	0.34	6.71
Asset Growth	-0.47	0.23	0.04	0.19	-0.34	-0.88	1.82	0.23	2.89	-3.38
ITA	-0.37	-0.18	0.72	0.06	-0.12	-1.30	-3.02	8.33	1.26	-2.87
Distress	0.44	-0.09	0.15	-0.12	-0.28	0.88	-0.78	1.16	-1.53	-4.19
O-score	-0.13	-0.09	0.14	-0.02	0.36	-0.24	-0.59	1.04	-0.31	4.96
GPP	0.20	0.22	-0.23	0.39	0.03	0.41	2.08	-1.74	1.96	0.40
ROA	0.07	0.13	0.47	0.50	-0.24	0.10	1.01	3.24	2.00	-1.97
CEI	0.66	-0.23	0.08	0.11	-0.06	1.45	-2.41	0.63	0.96	-1.02
Momentum	0.85	-0.12	0.22	0.13	-0.03	2.07	-1.42	1.74	2.59	-0.55
Liquidity	-0.13	0.02	0.05	-0.03	0.16	-0.45	0.43	0.64	-1.03	3.91

Table J.4: A Norwegian Composite Mispricing-model for OSE – Anomaly Portfolios

Notes: This table reports the estimation results of the Norwegian Mispricing (NOR) model for OSE from July 1998 through June 2018 (240 months). The model is estimated with long-short anomaly portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \beta_{i,3} MNOR_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{MNOR}	t_α	t_{RMRF}	t_{SMB}	t_{MNOR}
Beta	1.26	-0.76	0.09	0.05	2.96	-8.49	0.73	0.74
Size	1.61	-0.56	-1.01	0.01	3.46	-5.67	-8.30	0.07
BM	0.27	0.12	0.27	0.12	0.66	1.40	2.17	1.55
NSI	0.16	-0.04	-0.28	0.23	0.44	-0.67	-2.35	3.92
Accruals	0.10	0.35	0.00	0.02	0.21	2.67	-0.02	0.24
NOA	0.57	-0.16	-0.27	0.55	0.98	-1.41	-1.65	5.40
Asset Growth	-1.30	0.57	0.51	0.16	-2.46	4.83	2.82	1.51
ITA	-0.59	-0.10	0.78	-0.10	-1.61	-1.71	8.74	-1.51
Distress	0.83	-0.10	0.13	-0.48	1.69	-0.90	0.93	-5.89
O-score	0.46	-0.34	-0.19	-0.01	0.89	-2.56	-1.28	-0.06
GPP	0.64	0.36	0.11	-0.03	1.18	2.18	0.89	-0.41
ROA	-0.81	0.54	0.96	0.33	-1.37	2.84	6.90	2.82
CEI	0.54	-0.10	0.44	-0.03	1.14	-1.11	3.39	-0.35
Momentum	0.56	0.00	0.48	0.09	1.37	0.06	3.74	1.29
Liquidity	-0.13	-0.07	-0.15	0.13	-0.45	-1.76	-2.36	3.45

Table J.5: The Næs, Skjeltorp, and Ødegaard-model for OSE – Anomaly Portfolios

Notes: This table reports the estimation results of the 3-factor model of Næs, Skjeltorp, and Ødegaard (2009) for OSE. The model is estimated with long-short anomaly portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1}RMRF_t + \beta_{i,2}SMB_t + \beta_{i,3}LIQ_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{LIQ}	t_α	t_{RMRF}	t_{SMB}	t_{LIQ}
Beta	0.93	-0.59	0.27	-0.42	2.37	-6.41	2.31	-6.34
Size	1.17	-0.37	-0.81	-0.44	2.55	-4.78	-5.95	-4.22
BM	0.58	0.06	0.23	0.07	1.36	0.61	1.72	0.99
NSI	0.50	-0.04	-0.25	-0.14	1.32	-0.53	-1.98	-2.10
Accruals	0.54	0.17	-0.17	0.38	1.04	1.29	-1.24	3.48
NOA	1.31	-0.13	-0.18	-0.38	2.21	-1.16	-1.09	-3.06
Asset Growth	-0.10	0.16	0.12	0.84	-0.21	1.65	0.94	8.10
ITA	-0.64	-0.14	0.73	0.15	-1.91	-2.26	7.55	2.38
Distress	-0.12	0.02	0.19	0.03	-0.23	0.15	1.21	0.30
O-score	0.00	-0.14	0.00	-0.43	-0.01	-0.98	0.01	-4.94
GPP	0.67	0.32	0.08	0.09	1.10	2.81	0.47	0.48
ROA	0.65	0.11	0.58	0.76	0.95	1.09	2.80	3.75
CEI	0.39	-0.05	0.48	-0.09	0.86	-0.57	3.48	-1.04
Momentum	0.63	0.03	0.51	-0.10	1.55	0.34	3.82	-1.38
Liquidity	0.03	-0.06	-0.12	-0.11	0.09	-1.21	-1.77	-2.02

J.2 Factor Loadings for Value-Weighted Industry Portfolios

Table J.6: The Fama-French 3-factor model for OSE – Industry Portfolios

Notes: This table reports the estimation results of the 3-factor model discussed in Fama and French (1993) for OSE. The model is estimated with industry portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{HML}	t_α	t_{RMRF}	t_{SMB}	t_{HML}
10 Energy	-0.22	1.09	-0.03	0.22	-1.03	20.53	-0.62	5.68
15 Materials	0.16	1.09	-0.17	0.12	0.51	15.82	-2.11	1.96
20 Industrials	0.06	0.76	0.23	-0.09	0.20	15.12	2.84	-1.50
25 Cons. Disc	-0.66	0.93	0.44	0.03	-1.78	11.40	4.33	0.38
30 Cons. Staples	0.43	0.86	0.02	0.00	1.32	12.92	0.24	-0.02
40 Financials	0.27	0.87	0.14	0.03	0.86	11.95	1.80	0.50
45 IT	-0.72	1.44	0.42	-0.62	-1.51	13.28	3.44	-5.38

Table J.7: A Composite Mispricing-model for OSE – Industry Portfolios

Notes: This table reports the estimation results of the Stambaugh and Yuan (2017) M-3 model for OSE from July 1998 through June 2018 (240 months). The model is estimated with industry portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1}RMRF_t + \beta_{i,2}SMB_t + \beta_{i,3}UMO_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{UMO}	t_α	t_{RMRF}	t_{SMB}	t_{UMO}
10 Energy	-0.06	1.04	-0.15	-0.02	-0.29	20.47	-3.52	-0.58
15 Materials	0.34	1.08	-0.10	-0.12	1.12	16.15	-1.49	-2.37
20 Industrials	0.01	0.77	0.28	0.03	0.03	15.62	4.96	0.57
25 Cons. Disc	-0.52	0.89	0.37	-0.01	-1.49	11.39	4.80	-0.19
30 Cons. Staples	0.56	0.85	0.05	-0.09	1.69	12.84	0.71	-1.90
40 Financials	0.41	0.85	0.17	-0.07	1.28	12.82	2.90	-1.18
45 IT	-1.35	1.58	0.69	0.25	-2.59	13.32	6.25	2.25

Table J.8: A 4-factor mispricing model for OSE – Industry Portfolios

Notes: This table reports the estimation results of the Stambaugh and Yuan (2017) M-4 model for OSE from July 1998 through June 2018 (240 months). The model is estimated with industry portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1}RMRF_t + \beta_{i,2}SMB_t + \beta_{i,3}MGMT_t + +\beta_{i,4}PERF_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{MGMT}	β_{PERF}	t_α	t_{RMRF}	t_{SMB}	t_{MGMT}	t_{PERF}
10 Energy	-0.03	1.05	-0.09	-0.05	-0.03	-0.14	17.77	-1.57	-2.07	-0.88
15 Materials	0.23	1.08	-0.14	-0.04	-0.03	0.74	13.15	-1.75	-1.15	-0.68
20 Industrials	0.15	0.74	0.24	0.03	-0.06	0.52	13.91	3.16	0.76	-1.41
25 Cons. Disc	-0.40	0.90	0.38	-0.03	-0.03	-1.10	10.12	4.07	-0.61	-0.68
30 Cons. Staples	0.44	0.92	0.12	-0.07	0.05	1.34	11.70	1.32	-1.87	1.00
40 Financials	0.36	0.85	0.12	0.00	-0.02	1.11	11.53	1.60	0.04	-0.36
45 IT	-0.82	1.31	0.26	0.30	-0.22	-1.55	11.24	2.13	2.79	-2.58

Table J.9: A Norwegian Composite Mispricing-model for OSE – Industry Portfolios

Notes: This table reports the estimation results of the Norwegian Mispricing (NOR) model for OSE from July 1998 through June 2018 (240 months). The model is estimated with industry portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1}RMRF_t + \beta_{i,2}SMB_t + \beta_{i,3}MNOR_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{MNOR}	t_α	t_{RMRF}	t_{SMB}	t_{MNOR}
10 Energy	0.07	1.03	-0.05	-0.09	0.32	19.84	-1.06	-2.16
15 Materials	0.42	1.05	-0.19	-0.10	1.29	15.74	-2.50	-2.10
20 Industrials	-0.25	0.81	0.26	0.13	-0.85	15.29	3.14	2.59
25 Cons. Disc	-0.70	0.94	0.44	0.03	-1.93	10.90	4.23	0.45
30 Cons. Staples	0.53	0.85	0.02	-0.05	1.57	12.57	0.17	-0.87
40 Financials	0.50	0.84	0.12	-0.11	1.56	12.07	1.62	-2.17
45 IT	-1.46	1.58	0.50	0.22	-2.57	12.80	3.72	2.51

Table J.10: The Næs, Skjeltorp, and Ødegaard-model for OSE – Industry Portfolios

Notes: This table reports the estimation results of the 3-factor model of Næs, Skjeltorp, and Ødegaard (2009) for OSE. The model is estimated with industry portfolios as test assets. The factor loadings are estimated by OLS, with heteroscedaticity-consistent t-statistics based on White (1980), for each value-weighted test portfolio, i as

$$R_{i,t} = \alpha_i + \beta_{i,1}RMRF_t + \beta_{i,2}SMB_t + \beta_{i,3}LIQ_t + \varepsilon_{i,t}$$

where $RMRF_t$ is the value-weighted return on the market in excess of the 1-month NIBOR.

Portfolio	α	β_{RMRF}	β_{SMB}	β_{LIQ}	t_α	t_{RMRF}	t_{SMB}	t_{LIQ}
10 Energy	-0.24	1.11	0.01	-0.12	-1.08	20.10	0.19	-3.33
15 Materials	0.16	1.09	-0.15	-0.05	0.51	15.05	-1.69	-0.84
20 Industrials	0.22	0.68	0.15	0.20	0.78	13.54	1.83	3.76
25 Cons. Disc	-0.51	0.87	0.38	0.13	-1.39	9.71	3.63	2.33
30 Cons. Staples	0.44	0.86	0.02	0.01	1.35	11.99	0.18	0.20
40 Financials	0.34	0.84	0.11	0.05	1.03	11.01	1.38	0.93
45 IT	-0.28	1.21	0.16	0.70	-0.57	12.41	1.10	6.75