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Tails of Returns' Distribution and Expected Returns: An Empirical Study

Muhammad Kashif

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Muhammad Kashif

Asker, May 2023

Abstract

The classical literature of finance assumes investors as rational decision makers who maximize their wealth by conforming to the axioms of expected utility theory. It means that investors utility from a risky investment is equal to the expected utility which is estimated by weighting each outcome's utility by its probability. However, empirical findings from financial markets suggest that the expected utility theory as a descriptive theory of investors' decision making under risk may not hold true all the time. The prospect theory of decision making under risk suggests that investors tend to overweight their dislike of extreme negative outcomes. They often tend to prefer extreme positive outcomes with a small possibility over a normal outcome.

Deriving the motivation from these postulates, this thesis investigates investors preference towards positive returns in the Norwegian stock market. It also investigates the pricing of left tail risk in the US stock market. Firms that perform better on environmental, social and governance (ESG) aspect are marketed as investment prospects with lower tail risks. This thesis contributes to the understanding of tail risks associated with ESG investments. It further investigates the expected returns and the demand for ESG investments.

This thesis comprises of four articles in which quantitative methods are applied on the secondary data from the US and the Norwegian stock market. The first two articles apply different methods to identify market states and the repercussions of these states on the returns of investor seeking extreme positive returns and investors that take higher tail risk. The results from the articles suggest that both these phenomena exist, however, during some particular market states. The last two articles investigate ESG investments with respect to tail risks and investor demand and the results show that the demand of ESG investments is high and increased in recent years and these investments do not protect investors from tail risk.

Sammendrag

I klassiske finansteori antar man at investorer er rasjonelle beslutningstakere, som maksimerer formuen sin ved å tilpasse seg antakelsene til forventet nytteteorien. Det betyr at nytteverdien til en risikabel investering er lik den forventede nytten. Denne forventede nytten estimeres ved å vekte nytten av hvert utfall med sannsynligheten for det utfallet. Empiriske funn tyder på at beslutninger under forventet nytteteori ikke stemmer. For å bedre matche empiriske funn, det vil si hvordan mennesker faktisk tar beslutninger under risiko og påvirket av følelser, ble prospektteorien utledet. Denne teorien antyder at investorer har en tendens til å overvekte følelsene for negative utfall, og undervekte følelsene for et positivt utfall. For eksempel, for å kompensere smerten det er å tape 1000, man må vinne 2000. Mennesker overvurderer også sannsynligheten for ekstreme positive utfall med en liten mulighet fremfor et normalt utfall.

Med dette som et bakteppe, tar denne avhandlingen for seg preferansene til investorer og undersøker hvordan fordelingen til aksjer er fordelt i det Norske markedet, og hvilke faktorer som spiller inn på å forklare hvordan avkastningen påvirkes av forskjellige faktorer. Den undersøker også hvordan utfall langt til venstre, altså store negative utfall definert somvenstrehalerisiko, er fordelt i det amerikanske aksjemarkedet. Videre analyseres sammenhengen til denne venstrehalerisikoen og mål på bærekraft for bedriftene. Spesifikt ser jeg på om bedrifter som presterer bedre på miljømessige, sosiale og styringsmessige (ESG) aspekter, markedsføres som investeringer med lavere halerisiko. Med dette bedrar denne oppgaven til forståelsen og driverne av halerisiko generelt, og sammenhengen til ESG-nivået til bedriftene spesielt.

Denne oppgaven består av fire artikler som anvender kvantitative metoder på sekundærdata fra USA og det norske aksjemarkedet. De to første artiklene bruker forskjellige

metoder for å identifisere såkalte regimer i markedet, samt og virkningene av disse regimene på avkastningen til investorer som har en større andel investert i aksjer med stor sannsynlighet for ekstreme utfall i forhold til andelen slike selskaper totalt. Resultatene fra artiklene tyder på at begge disse fenomenene eksisterer, men stort sett bare under noen bestemte tilstander i finansmarkedet. De to siste artiklene undersøker ESG-investeringer med hensyn til denne typen halerisiko og etterspørselen etter slike investeringer. Resultatene viser at etterspørselen etter ESG-investeringer er høy og økt de siste årene, men at denne typen investeringer beskytter ikke mot ekstreme utfall, altså halerisiko.

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Chapter 1

Synopsis

Summary of the Thesis

1.1 Introduction

Stocks or shares represent ownership share in a corporation. Stockholders are entitled to receive dividends that a firm may pay and are the residual claimants on a firm's real assets. Stockholders' benefit depends on mainly two things: first, the dividends they receive that the firm decides to pay and second, the increase in price of the shares if that firm performs good. These benefits should be in accordance with both the time that their money is bound and the risk of the future. This benefit is the return of equity investors and the aforementioned two factors constitute the risk of their investment. Return on a stock is a function of its price. If a stock is priced more (less) than it's worth then it is very likely that the return on that stock will be lower (higher) in the future. Risk of an investment usually stated as the likelihood of deviation of realized return from the expected return.

The entire subject of finance permeates the paradigm of risk and return. Both, the risk and the return lie in the future, and are latent variables. It means that we cannot observe them directly from market data; thus, we need some econometric model to estimate them. We use realized data in some econometric model to estimate expected risk and expected return by taking some assumptions on the distribution of expected return. The risk estimate is a proxy of actual risk since we cannot measure actual risk.

Risk is categorized into different types but can be summarized into two forms; One, risk which is associated to individual security (idiosyncratic risk) and second, risk which is associated to market as a whole (systematic risk). In case of individual stocks, specific risk that affects the returns on that individual firm's stock for example strike of employees can affect expected profitability of that particular firm. Risk as being deviation from expectation does not mean the possibility of bad outcome only, it also includes variation towards better than expected outcome. Variance, specifically standard deviation, can be a good estimator of risk implied that the returns' distribution is normal but empirical evidence suggests that extreme values are more common in economic data than that of natural data.

Classic finance theories, including those proposed by Markowitz (1952), Sharpe (1964), Lintner (1965) and Mossin (1966), assume that investors are risk-averse and utility maximizers. Under the expected utility theory, investors favor investments with higher expected returns for the same level of risk and opt for lower volatility investments when expected returns are equal. These theories also suggest a symmetric and normal distribution of returns, characterized by mean and volatility. Intuitively, investors appreciate positive deviations from expectations and dislike deviations below the mean.

Prospect theory, introduced by Tversky and Kahneman (1979) , challenges these assumptions by examining decision making under uncertain outcomes. Their experimental studies reveal that investors often prefer lotteries with small chances of extremely high returns, even when their expected returns are negative, compared to lotteries with positive expected returns but no possibility of extremely positive returns. Researchers like Arditti (1967) and Scott and Horvath (1980), Kane (1982) and Harvey and Siddique (2000) have expanded the traditional paradigm of mean and variance of returns to include skewness and kurtosis. Although some of these studies remain within the expected utility theory framework, others draw motivation from prospect theory, highlighting the psychological aspects of investor decision making that lead them to choose stocks with a small probability of significant payoffs.

The difference in the assumption about what drives investors to choose a prospect with positive skewness has an impact on the descriptive behavior of investors. As per the implication of expected utility theory investors' utility which comes from choosing a prospect with positive skewness is included in the estimation of expected utility from that prospect. Which means that if the expected value is negative after considering the effect of skewness the prospect does not worth it. On the other hand, prospect theory implies that investors prefer positive skewness even if the expected utility is negative. This skewness preference behavior is also termed as lottery seeking behavior of investors. Bali et al. (2011) argue that the stocks that have some probability of paying extreme positive returns act as lottery for investors and show that lottery preference is significant in the US market. The authors named this phenomenon as the MAX effect. In our first article, I along with Thomas Leirvik, investigate this lottery seeking behavior of investors in the Norwegian stock market. Kumar (2009) finds that investors' preference for lottery like prospects is strongly affected by the state of overall economic conditions and socioeconomic conditions of investors. Their empirical evidence is in line with the descriptive propositions of the prospect theory on how people choose lottery like prospects. We also explore influence of the state of oil market on the MAX effect.

Another aspect of prospect theory that tweaks the expected utility theory in a way how investors consider negative outcomes below some psychological threshold, see for example Fishburn and Kochenberger (1979). The prospect theory suggest that people consider losses and gains differently in a way that they dislike losses more strongly the they like gains. Since variance is considered risk in classical finance literature Markowitz (1959) argued that only the semi-variance which is estimated only from the deviations below the mean should be considered risk of an investment. Bawa (1975), Bawa and Lindenberg (1977) and Price et al. (1982) propose that investors have some threshold in their mind that they would not like as an expected outcome, for example an investor is willing to invest in an asset with lowest point as 20 percent below mean but is not willing to invest in any asset that has some some probability of below 20 percent negative returns. The argument suggests that investors have some threshold of maximum bearable loss on their portfolios and assets that have a probable outcome below that threshold are excluded from the portfolio. These assets are discounted at a level that their prices are lower enough to get a buyer that means they should command a higher risk premium because of their higher downside risk. Downside risks also comprise of tail risks because they entail outcomes that lie in the left tail of returns' distribution. Often times the terms downside risk and tail risk are used interchangeably. Ang et al. (2006), Kelly and Jiang (2014) and Bali et al. (2014) investigate tail risks in the US market via various estimators. Assets that produce poor results at the same time when the market is doing poorly are considered assets with higher tail risks because their payoffs decrease right at the time when investors' need payoffs run high. Motivated by this strain of literature, our second article investigate the pricing of this type of risk in the US during different regimes of overall stock market.

Sustainable investments are commonly defined as investments that incorporate considerations of environmental, social and governance (ESG) aspects other than risk and return. In recent years, there has been a substantial expansion in the body of literature pertaining to environmental, social, and governance (ESG) investments, particularly following the unanimous endorsement of sustainable development goals by the United Nations in 2015, see for example Luo et al. (2022). ESG investments are marketed as a way to hedge tail risks because of their higher performance on the ESG criteria, see for example Van Duuren et al. (2016), Broadstock et al. (2021), Lööf et al. (2022) and Mohanty et al. (2021). In the third article, I investigate tail risks of sustainable investments. The proposition that the firms that consider ESG criteria in doing their business should be less prone to adverse ESG events such as water shortages, climate change, employee strike, pressure from interest groups, less corruption etc. in comparison with the firms that do not do well on ESG criteria. This proposition suggests that high ESG firms contain lower ESG related risks than that of lower ESG firms and translating it into the risk and return paradigm suggests that high ESG firms should have lower returns while low ESG firms should command higher returns. However, recent empirical evidence is contrary to this proposition and show that investments in high ESG firms produce higher returns than that of investments into the firms that perform poorly on ESG criteria, see for example Eccles et al. (2014) and Madhavan et al. (2021). The fourth article explore the expected returns of sustainable investments with a lens of investor demand.

This thesis comprises of five chapters with synopsis as the first chapter and the remaining four chapters are structured as each chapter represents one research article. Synopsis provides the reader a birds eye view of the research questions, relevant theories, data and methodology, philosophical reflections on the research conducted and an overview of the articles.

1.2 Portfolio theory

The term "modern portfolio theory" (MPT) refers to the groundbreaking work of Markowitz (1952), where the author proposes a method for selecting securities in a portfolio. According to the theory, the expected return on a single risky asset is defined as:

$$E(r) = \Sigma_{s=1}^{n} p(s)r(s) \tag{1.1}$$

$E(r)$ is expected return on a risky asset, $r(s)$ is the return on asset in the case of scenario s, $p(s)$ is the probability of scenario s happening and n represents number of expected scenarios. The distribution of returns on risky asset is assumed normal and variance (σ^2) is considered the risk of that asset which is estimated via equation 1.2.

$$\sigma^2 = \Sigma_{s=1}^{n} p(s)[r(s) - E(r)]^2 \tag{1.2}$$

Creating a portfolio of two risky assets named A and B makes the return on the portfolio as follows:

$$r_p = w_A E(r_A) + w_B E(r_B) \tag{1.3}$$

Which is simply the weighted average of expected return on the two assets where w_A and w_B represent fraction of wealth invested in asset A and B respectively. However, the risk of the portfolio becomes:

$$\sigma_p^2 = w_A^2 \sigma_A^2 + w_B^2 \sigma_B^2 + 2 w_A w_B \sigma_A \sigma_B \rho_{AB} \tag{1.4}$$

While the expected returns of a portfolio is a linear combination of how much is invested in each asset and depend only on the expected returns of each asset, the risk of the portfolio is nonlinear, and depends on the risks of each asset as well as the correlation between the assets. This means that the total portfolio risk can in certain scenarios be smaller than each individual asset's risk:

$$\sigma_p < min(\sigma_A, \sigma_B) \tag{1.5}$$

However, the requirement for equation 1.5 is that the correlation between the assets is negative. If, however, the correlation between assets equals one, then the portfolio risk is the weighted average risk of the assets. If the correlation is perfect negative, -1, then it is possible to eliminate risk from the portfolio. Both these cases are rare in practice.

Nevertheless, the discovery that including an asset to a portfolio can reduce the overall risk of the portfolio led to a shift in how both researchers and practitioners think about investing. The act of combining many assets into a portfolio to reduce risk is termed diversification. The thinking went from stock-picking, to portfolio construction. There was a boom in scientific research showing that it is possible to optimize the construction of a portfolio both with respect to minimize the risk of the portfolio, or to maximize the returns per-unit-of-risk, termed as risk-adjusted returns, and how to allocate optimally if one requires a specific return per year, or if one is not allowed to borrow. It was also quickly discovered that there is a limit to how much it is possible to diversify: for each additional asset included in a portfolio, the marginal reduction in overall risk diminishes and eventually reaches a threshold: the systematic or non-diversifiable level of risk.

The optimization problem presented in the seminal work of Markowitz (1952) is deemed highly intricate and challenging to solve due to the substantial quantity of risky assets existing in the financial market. Capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) address this intricate issue of determining an asset's risk premium by considering its relationship with market-wide risk. According to CAPM, an asset's risk premium is dependent on its contribution towards the overall market risk. CAPM's proposition is considered a fundamental pricing principle of risky assets where the expected return on risky asset is estimated as their contribution to non-diversifiable risk also termed as market risk or systematic risk and diversifiable/idiosyncratic/firm-specific risk is not rewarded.

$$E(r_i) = r_f + \beta_i[E(r_M) - r_f] \tag{1.6}$$

where $E(r_i)$ is expected return on stock i, β_i is stock i's contribution to the market risk, $E(r_M)$ is expected return on the market of all risky assets. Here β_i is:

$$\beta_i = \frac{Cov(r_i, r_M)}{\sigma_M^2} \tag{1.7}$$

In practice realized returns on a stock are used as a proxy of expected return on that stock, realized return on a market index is used as a proxy for expected returns on the overall market and CAPM's beta is estimated using a linear regression where an asset's returns are regressed against the returns on a market index. Therefore return on an asset's pricing equation according to CAPM becomes:

$$R_i(t) = \alpha_i + \beta_i R_m(t) + \epsilon_i(t) \tag{1.8}$$

R_i is excess return (risk premium) on stock or portfolio i $(r_i - r_f)$, α_i is excess return on asset or portfolio i when the market risk premium $(R_i(t) = r_M - r_f)$ is zero and ϵ_i is the error term having normal distribution with zero mean and σ standard deviation.

The CAPM is based on strict normative assumptions, such as the idea that all investors are rational decision-makers within the mean-variance framework of Markowitz (1952). Moreover, the CAPM assumes that investors have uniform expectations, all assets in an economy are tradable, information acquisition is costless, and there are no trading costs. However, in practice realizations of returns are used as proxies of expected returns to estimate CAPM predictions implying that these normative assumptions are assumed at a descriptive level of investor decision-making. At the normative level, simplified assumptions must be made to develop a model, as it is impossible to account for all the complexities of the real world. Rejecting the CAPM at a normative level means rejecting the foundational assumptions of the model. However, if we were to reject economic models based on their normative assumptions, no economic model would withstand such a scrutiny. As a result, asset pricing models are primarily rejected by the empirical performance of their predictions.

In essence, CAPM posits that the overall market portfolio is a tradable asset and the most efficient portfolio and an asset's risk premium is proportional to how it co-moves with the market portfolio. It means that if a stock has a significantly positive α value it is considered to be under-priced and equilibrium risk premiums according to CAPM ordains that investor buy this stock to raise its price to a level that the α disappears. In other words, the market is at equilibrium when prices of assets reflect their sensitivities to the market. The CAPM does not work well in practice and empirical evidence against it piled up not long after its proposition. Researches proposed various systematic risk terms to improve upon the CAPM.

1.3 Arbitrage Pricing Theory and Factor Models

The Arbitrage Pricing Theory (APT) is an alternative asset pricing model to the CAPM. It was developed by economist Stephen Ross, see Ross (1976). The APT aims to determine the expected return of an asset by considering multiple factors that affect the asset's return, as opposed to the CAPM, which uses only one factor (market risk) to predict the expected return. Ross (1976) developed arbitrage pricing theory (APT) is based on the law of one price which claims that two assets that are equivalent in all risk characteristics must have same price. Arbitrage is defined as risk-free payoff which one can obtain from trading two assets that are equivalent in all economic aspects but have different prices. As per CAPM, if two stocks have same sensitivity to the market risk then they should earn the same returns in other words there is only one factor that determines the price of these stocks. APT assumes that there are enough number of stocks to diversify away firm-specific risks and an arbitrage opportunity cannot persist in a well functioning and efficient market. The APT is based on the idea that the expected return of a financial asset can be explained by its sensitivity to various macroeconomic factors, such as interest rates, inflation, and GDP growth. These factors are represented by a set of systematic risk factors, and each asset has a specific level of exposure to each of these factors. The exposure of an asset to a particular factor is represented by its factor beta, which measures the sensitivity of the asset's return to changes in the factor.

According to the APT, the expected return of an asset is given by the following equation:

$$E(r_i) - r_f = \alpha_i + \beta_{i1}F_1 + \beta_{i2}F_2 + ... + \beta_{in}F_n + \epsilon_i \tag{1.9}$$

In equation 1.9, $E(r_i)$ is expected return on asset i and r_f represents the return on a risk-free investment, such as a government bond. The factor betas $(\beta_1, \beta_2, ..., \beta_n)$ represent the sensitivity of the asset's return to each factor, and the factor risk premiums $(F_1, F_2, ..., F_n)$ represent the additional return required for taking on the risk associated with each factor.

One of the key advantages of the APT over the CAPM is that it can accommodate multiple sources of systematic risk, making it more flexible and potentially more accurate in predicting asset returns. However, the APT does not provide a definitive list of factors that should be included in the model, which means that the choice of factors and the estimation of factor betas can be challenging for practitioners.

Fama (1970) propose efficient market hypothesis (EMH) which claims market prices fully reflect information available in the market and no one can consistently beat the market by forecasting prices or returns. According to EMH, stock prices follow Random Walk. Random Walk in this context refers to the idea that in a stock price series each successive price change represents a random departure from previous price. The idea asserts that if flow of information is not hampered, information is immediately reflected in equity prices, therefore, today's stock price movement is a reflection of today's news and this movement is independent of last day price. By definition, news cannot be predicted consequently stock price movements are purely random and unpredictable, hence returns on stocks cannot be predicted.

The conclusion of CAPM and efficient market hypothesis is similar in a sense that only systematic risk is rewarded and the best strategy to invest is to invest in the market portfolio. APT reaches the same regression equation 1.8, however, taking different assumptions of the process on how equilibrium prices are determined. APT stresses that if the asset is a well diversified portfolio then the error term in the regression equation is zero and if that portfolio has a large α then either it is a mispricing or there exist other systematic risk factors that are missing in the model. Zero α means that prices or risk premium of a security is at equilibrium and satisfy no arbitrage condition.

CAPM fails miserably in the empirical tests, however, its basic propositions are still valid. It is not an asset's volatility or payoffs in isolation which determines its risk, in fact, it is how the asset pays-off relative to the prevailing situation in the market. Investors are better off when they hold a diversified factor such as the market factor of CAPM instead of holding an individual security. The market factor represent the macroeconomic factor and investors cannot diversify away the market risk. Assets that payoff during the bad times provide lower risk premiums than those that payoff in good times. The bad and good times are factor specific for example bad times for CAPM is when the market portfolio crashes or declines. In the field of financial economics, the inclusion of a factor within an asset pricing model necessitates a solid foundation in economic theory, such as the market factor. This factor is considered integral due to its inherent intuitive justifications. Consequently, the CAPM continues to find application within academia as a means of estimating expected returns, as evidenced by Welch (2008).

Factor models are quantitative tools used in finance to explain the relationship between the return of an asset or portfolio and various underlying factors that drive the asset's performance. These models help investors and portfolio managers understand the sources of risk and return, allowing them to make informed investment decisions, construct well-diversified portfolios, and manage risk effectively. In a factor model, the return of an asset is expressed as a linear combination of multiple factors, with each factor having a specific weight (or beta) that represents the asset's sensitivity to that factor. Factors are typically macroeconomic, fundamental, or statistical in nature, and they are chosen based on their ability to explain the variation in asset returns.

There are three types of factors commonly used in finance: Macroeconomic, fundamental and statistical. Macroeconomic factors are based on macroeconomic variables, such as GDP growth, interest rates, and inflation, to explain the variation in asset returns. The rationale behind using these factors is that the performance of financial assets is influenced by the overall economic environment. The models based on fundamental factors focus on firm-specific characteristics, such as earnings, dividends, and book-to-market ratios, to explain the variation in asset returns. These models are often used in equity research and portfolio management to identify stocks with attractive risk-return profiles. Statistical factors are derived by using statistical techniques, such as principal component analysis (PCA) or factor analysis, to identify common patterns in asset returns. The resulting factors are often referred to as "statistical factors" or "latent factors," as they are not directly observable. These factors do not have a clear economic interpretation and, consequently, have not gained significant popularity within academia.

Multi Factor models are asset pricing models where more than one factor is assumed to drive the risk premium of assets. Most of the factors are based on economical rationale which is based on either rational decision making of investors or on the proposition of behavioral finance. Rationality argument proposes that a factor's risk premium is a compensation of its poor performance in some specific times, whereas, behavioral argument suggests that a factor's risk premium is a consequence of some aggregate behavior of investors which is not arbitraged away by the rational investors, see for example Ang (2014)

Factors that are based on characteristics dominate the field of asset pricing due to their empirical appeal and validity. Characteristics are accounting variables such as market capitalization, book value to market value ratio, dividend yield, investments etc. Fama and French (1993) propose two systematic risk factors in addition to CAPM market factor based on their empirical findings of the size effect by Banz (1981) and book value to market value ratio effect by Rosenberg et al. (1985). The first additional factor is formed on the basis of empirical over-performance of firms that have smaller market capitalization in comparison with firms that have higher market capitalization and called SMB factor. SMB which stands for small minus big is a well diversified tradable portfolio which results from buying stocks of small firms and simultaneously selling stocks of big firms. The second factor is called HML which stands for high minus low and it results from buying stocks of firms that have higher book to market value ratio and simultaneously selling stocks of firms that have lower values of book to market value ratio. This strategy of buying and selling (long and short position) of well diversified portfolios of same value at the same time produces some α values that can not be attributed to CAPM market risk factor. Fama and French (1996) show this empirical evidence as the rejection of CAPM and propose asset pricing model as:

$$R_i(t) = \alpha_i + \beta_{iM} R_m(t) + \beta_{iSMB} SMB(t) + \beta_{iHML} HML(t) + \epsilon_i(t) \tag{1.10}$$

The authors provide a risk based justification of these two factors that are assumed to proxy for some systematic risk. The argument suggests that the higher returns on small firms' stocks is due to the additional risk that small firms face in acquiring resources in comparison with big firms and small firms are more likely to fail than that of big firms due to little asset holdings. Stocks of firms with high book to market value ratio are termed as value stocks and stocks of firms with low book to market value ratio are termed as growth stocks. The argument suggest that value stock earn higher returns because they are more riskier reason being the low value in comparison to assets represent bad performance of a firm.

Opponents of a risk based justification claim that this out-performance of small and value stocks over big and growth stocks respectively is because of mispricing of assets, see for example Lakonishok et al. (1994), Griffin and Lemmon (2002) and Hirshleifer et al. (2012). They claim that low book-to-market stocks are overpriced and high book-to-market stocks are under-priced. They argue that out-performance of small firms' stocks over big firms stocks is due to mispricing, reason being small stocks gets limited analysts coverage and these small firms' weak fundamentals and non-availability of data make them difficult to price correctly. These justifications also seem intuitive as the author claim that these factors are anomalies in stock returns.

The number of factors that are claimed to explain risk premium on stocks has exploded in recent years, for example Green et al. (2017) tested 94 characteristics to see if they are priced in the cross-section of stock returns. Cochrane (2011) named this numerous number of factors as factors zoo and argues that most of these factor lack replication-ability. More recently Jensen et al. (2021) provide evidence that these factors can be replicated. Ang (2014) argues that it is the fact that empirical advances in asset pricing literature rejects most of the asset pricing models such as CAPM, however, it opens the avenues to new knowledge, new sources of risk premiums and ways to manage risks. In asset pricing literature there is a dominance of using empirically motivated models such as Fama and French (1996) three factor model, Fama and French (2015) five factor model with the addition of Carhart (1997) momentum factor and Hou et al. (2015) q-factor model. A new factor is assumed to be a proxy for some kind of systematic risk or some anomalous behavior of investors if it produces some α even after accounting for factors that are already discovered.

A factor which produces premiums in the cross-section of stocks returns can be a manifestation of systematic risk or signifies a mispricing which is driven by behavioral biases of investors. Such a factor has implications for the pricing of stocks. The pricing equation associated with this phenomenon can be expressed as follows:

$$P_i = \frac{E(payoff_i)}{1 + E(r_i)} \tag{1.11}$$

Where the current price of stock is estimated by discounting the future payoff of a stock by expected return. In the case of CAPM, $E(r_i)$ is driven by only the market factor and in Fama and French (1996) three factor model, it is driven by the market factor, SMB and HML.

1.3.1 Tail Risk

For a factor which is driven by systematic risk, it is imperative that the factor produces bad results during some times which is the reason that it commands a risk premium in some other times. In case of CAPM, a stocks risk premium is dependent on the factor loading on the market factor which translates into risk premium is driven by the stock's lower payoffs during the market downturns. However, the factor loading is estimated taking all observations of the market and the stock which means that higher value of factor loading when a stock co-moves with the market either during the downturns or when the market is actually growing. However, investors dislike when their portfolio co-moves higher than the market during downturns and prefer higher co-movements of their portfolio when the market grows. But CAPM's beta considers both co-movements as risk. This rationale give rise to the argument that investors consider outcomes that lie below some threshold in the returns distribution as investment risk.

Markowitz (1959) considered this rationale and argued that instead of using variance as a measure of risk, one should measure risk by using observations that fall below mean which is referred as semi-variance or lower partial moment. Bawa and Lindenberg (1977) develop CAPM based on mean-lower partial moment paradigm where they consider observations that fall below the risk free rate. Ang et al. (2006) show that the market prices beta which is estimated by only taking account of the observations that are below the mean. The authors termed this phenomenon as investors disliking of downside risk.

Bali et al. (2009) and Bali et al. (2014) argue that tail risk and downside risk differ in a sense that downside risk assumes that risk premiums are driven by investors' dislike towards outcomes that are below mean whereas tail risks are associated with the outcomes that lie deep in the tails of returns' distribution such as outcomes that are more than three standard deviation below the mean. However, tail risk measures are categorized as measures of downside risk. Roy (1952) argue that investor acknowledge that risk premium is driven by bad performance of some time and do not worry much about some level of volatility instead they are more concerned about outcomes that are below their level of tolerable negative outcome. The author suggests that investors invest build their portfolio on their dislike of outcomes that are below their threshold level and termed this phenomenon as safety first principle.

Ang et al. (2009) and Baker et al. (2011) provide evidence that there is no premium for volatility. This empirical evidence builds on the argument that investors perceive values below their predetermined thresholds as risk, while volatility within those thresholds is not accounted as risk. Bali et al. (2009),Kelly and Jiang (2014) and Bali et al. (2014) find that tail risk measures such as value at risk, expected shortfall, tail risk betas, lower partial moment are priced in the cross-section of stock returns. The second articles with is a joint work of Thomas Leirvik and me contribute in this line of literature. The third article, which is a solo work also contribute in this stream of literature where downside risks of ESG investment are investigated.

Behavioral Finance and Extreme Events

The empirical evidence which is evident from the market crashes such as 2008 global financial crisis indicate that irrational behavior of investors is a reality. This reality is not accommodated in the realm of classical asset pricing literature especially in EMH. CAPM's major innovation was that assets are not priced in isolation instead pricing is a function of relative behavior an asset with respect to the market which is a descriptive aggregation of investors decisions. This argument questions the normative validity of rational behavior of investors. Behavioral finance critiques financial theories' non-consideration of how people actually make decisions and peoples decisions whether rational or irrational make a difference.

Behavioral finance literature shows us that investors make irrational decisions. These sub-optimal decisions affect asset prices that rational decision makers may exploit to gain profits Therefore, irrational behavior of investors is not a sufficient condition to prove that the capital market are inefficient. This argument is countered by another stream of behavioral finance literature that shows the existence of limits to arbitrage in the market. The argument suggests that in theory rational investors arbitrage away the price differences occur due to irrational investors, however, it involves a rational investor to dis-allocate resources from other positions and the risk still remains that the irrational price does not converge to intrinsic value of asset during the investment horizon. The limits to arbitrage are higher in the presence of limitations on short selling and higher costs of borrowing money, see for exmple Barberis and Thaler (2003). The critique of the behavioral finance is that it explains the irrational behavior of investors and how prices may not reflect intrinsic value but it does not guide investors in their main objective; how to make money in the market, see for example Fama (1998) and Cooper et al. (2001).

1.3.2 Stocks as Lotteries

The prospect theory drives evidence from the experiments and argues that risk averse investors engage in a game of lottery because of skewness. see for example Tversky and Kahneman (1979) and Kahneman and Tversky (1984). The argument claims that risk averse agents choose to gamble knowing that the expected returns are negative. This phenomenon has a long history in the literature about gambling and the game of chances, see for example Thaler and Ziemba (1988). However, Kumar (2009) investigates this phenomenon in the stock market. He gathered the demographics of lottery players and finds that these agents are also more likely to invest in stocks that have lottery like features. He defines lottery-like-stocks as the stocks that are priced less than 5 dollars and have high level of idiosyncratic volatility and skewness. Bali et al. (2011) investigate the preference of lottery like stocks in the US market and find that lottery like stocks have lower mean returns, however, they define lottery like stocks as the stocks that have highest level of daily returns in a given month. The first article of this thesis investigates preference for lottery like stocks in the Norwegian market.

Prospect Theory and Tail Events

Tversky and Kahneman (1979) proposed a descriptive theory of investors' behavior as a critique of expected utility theory (EUT). They argue that people often make irrational decisions under risk. They challenge the assumption of human rational behavior especially in the field of economics and finance. They explain that humans tend to make decision to the complex problems where uncertainty is involved based on heuristics. Heuristics are simple rules that people use to form judgments. These mental shortcuts can lead to systematic cognitive biases that results in deviation from optimal outcome.

Prospect theory (PT) also critiques EUT as normative theory under risk and uncertainty. If we assume EUT as valid normative theory, any reasonable person would want to make decisions that do not violate axioms of EUT, thus, he/she does not lose propositions. The idea that individuals wish to make decision based on EUT, albeit in practice they often do not, is the basis of loss of normative appeal of EUT. Hence, normative application of EUT in decision-making under risk depends on the descriptive validity of EUT. They claim that people see investment problems as prospects of gains and losses contrary to EUT where people are concerned about maximizing net wealth by adding up the product outcomes and probabilities of their occurrence.

PT explains that the cognitive biases are stronger when it comes to extreme events. People often tend to overweight events that have very small probability of occurrence. Tail events are such events that have very small probability of occurrence. The implication of this phenomenon in investment decisions is mispricing of stocks, which consequently leads to arbitrage opportunities. For example, there is a one percent chance that a stock return will be three standard deviation towards right side from mean. Over-weighting of this small probability leads to higher price of the stock, hence, lower return in the future. Similarly, if there is a stock that has a very small probability to be three standard deviation towards left side from mean. Over weighting of this small probability will lead to lower price of the stock, hence, higher return in the future.

1.4 Data and Methods

Researchers categorize data into two categories, primary and secondary, based on the process of acquiring the data. Primary data is defined as the first hand data which is created by the researcher or its team in the process of their research for example survey results. Secondary data is defined as the data that has already been collected by someone other than the research team for their research or general purpose for example stock market prices data. This thesis employ only secondary data to test hypotheses by applying econometric methods and decision is made on the basis statistical inference.

1.4.1 Portfolio Analysis

The portfolio method is most widely used method in the field of empirical asset pricing which tests cross-sectional relationship between two or more variables (Bali et al., 2016). The analysis is applied in thesis articles in a way that portfolios are created of common stocks by sorting stocks on a concerned variable, such as MAX in the first article where each portfolio is diversified and represents different level of sorting variable. Then returns (the second variable of concern) for each portfolio are calculated for the next period for example next month for different weighting scheme for example equal weighting of all stocks in the portfolio. The the relationship is tested whether the variation in the one variable (sorting variable) explains the variation in the second variable; returns. This analysis gives us the understanding of the cross-sectional variation between two and more variables. The most important benefit of portfolio analysis is that it is does not assume any distribution of the relationship between the variables under investigation. It is a non-parametric method which is also helpful in discovering non-linear relations between the concerned variables. However, to test the hypothesis that returns on one portfolio are different from another portfolio a Student's t-test is applied. The only drawback is that it is difficult to control other variables' influence on the relationship which is being tested for example in the discovery of a new factor one has to control for a large number of other factors that are priced in the stock market.

1.4.2 Regression Analysis

In a regression analysis, we test a relationship between dependent variable and independent variables. Unlike portfolio analysis, we can add a number of other factors to control for their effect on the relationship of concern. A drawback of this analysis is that we have to assume a nature of relationship between dependent and independent variables for example linearity in case of most empirical asset pricing models such as CAPM and Fama and French (1996) three factor model. We apply ordinary least square and weighted least square regressions in this thesis articles. Fama and MacBeth (1973) method is applied which is like a panel regression where first cross-sectional regressions are run each period to estimate time-series of regression coefficients then in the second step Student's t-test is applied on whether the means of the coefficients are different from zero.

In the Student's t-test of portfolio analysis and regression analysis the data consists of a number of stocks and for a number of years. This type of data suffer from the problems of heteroskedasticity and auto-correlation that affect the estimation of standard errors. Therefore, Newey and West (1994) method is applied to correct the standard errors which gives us *t-stats* and *p-values* after accounting for these issues.

For the first article, we collect daily stocks prices and adjusted prices data for all stocks that are and have been registered on Oslo stock exchange as well as risk free rate data from the TITLON database. The data spans from January 01, 1996 to December 31, 2016 The book to market ratio data are collected from Thomson Reuters Datastream. The data for Norwegian Fama-French Factors is collected from Bernt Arne Ødegaard online data library. Brent oil prices data is collect from United States Energy Information Administration website. This data are used to test research questions; whether the MAX as a proxy of investors preference for lottery like stocks is priced in the Norwegian market and Is the state of the oil market affects the relationship between the MAX and expected returns?

The second article's data consists of daily prices and returns data of all the stocks registered on US stocks markets from January 01, 1980 to December 31, 2016 that is sourced from CRSP database. Accounting data fetched from Green et al. (2017) online data library. Factors data and risk-free rate data comes from Fama-French online data library. The data are employed to find answer to research question that whether tail risk measured as lower partial moment is priced during low and high volatility regimes in the market?

For the third article I collect daily prices and returns data from FactSet prices data-feed from January 01, 2007 to December 31, 2021. Accounting data comes FactSet fundamentals data-feed and ESG ratings from Truvalue Labs data-feed. Identification variables to confirm that the stocks data belong to the US common stocks come from FactSet ownership data-feed. Factors data and risk-free rate data comes from Fama-French online data library. The Data is used to answer research questions; do ESG ratings command a premium and Do the higher ESG rated portfolio posses lower tail risks in comparison with lower ESG rated portfolio? The fourth articles also employ the same data with some additional data on the ownership of stocks in the US market which comes from FactSet ownership data-feed. I employ data of quarterly Form-13f filings to find the ownership stakes of individual stocks. This data is used to answer research questions; Do the stocks of firms that over-perform on ESG criteria has higher demand than the stocks of firm that under-perform on ESG criteria?, Is there a relationship between ESG ratings and expected returns during different sample periods? and Can ownership from active institutional investors explain the returns on high ESG rated stocks?

1.5 Philosophy of Science

Kuhn (2012) in his book “The Structure of Scientific Revolutions” (first published in 1962) explained the development of science. He explains the concept of paradigms in the development of science. A paradigm, according to Kuhn, represent a set of theories, concepts, research methods, thought patterns or postulates that constitute a field of science. He also explains the idea of paradigm shift when a fundamental change occur in the old paradigm and new paradigm emerges. A science can be in old paradigm or in new paradigm but leaving the paradigm means killing the science itself.

According to Kuhn, there is existence of alternating phases in mature science; it goes through phases of normal science and revolutions. In normal science the key theories, concepts, values, assumptions and standards that comprise the disciplinary matrix remain unchanged. It allows cumulative generation of puzzle-solutions, however, in case of scientific revolution the disciplinary matrix is subjected to revision so solution to the serious anomalous puzzles are permitted that cannot be explained by the preceding normal science.

CAPM's validity is based on the assumption of rational and independent decision making of investors. Based on the same principles, EMH claims that market prices are correct and they reflect fundamentals and rational expectations of investors. Shiller (2003) argue that there is evidence of investors' trading on feedback. When prices go up based on a speculation, they create successes for some investors which may attract public attention and promote word-of-mouth enthusiasm. The attention of public and feedback-enthusiasm raise expectations for price increases in the future. If this feedback-loop is not interrupted, prices become unsustainably high which is termed as price-bubble in the market. Then, eventually the bubble bursts and unsustainably high prices drop suddenly because they only represented expectations of further prices increases rather than fundamentals. These high prices during the market bubbles are evidence of irrational behavior of investors. The incapability of CAPM and EMH to explain market bubbles can be considered what Kuhn called the crisis period in science.

Development of PT and the field of behavioral finance can be considered as a paradigm shift. Behavioral finance explain the puzzle of market bubbles and other extreme events that did not be explained by the paradigm of EMH. PT focuses more on the psychological processes involve in decision-making. Kuhn's concept of Incommensurability seems valid as PT can not be considered as improvement of EUT. EUT deals with how a person should decide on propositions in the presence of risk and uncertainty. On the other hand, PT is presented as a descriptive theory of decision making under risk meaning it describes how people violate the principles of rationality using heuristics. Same as, promulgation of behavioral finance cannot be considered an improvement to EMH as behavioral finance deals with some special cases that are anomalous to EMH. PT does not falsify EUT completely, it rather argues to account for psychological processes, an individual goes through while making a decision involving risk, that EUT is not able to account for. This can be considered a paradigm shift where the ontological assumption of rational economic decision-making is relaxed to account for irrational behavior of humans as well.

Falsification is a concept given to us by Popper (2005). Hands (1993) evaluates the falsification concept of Popper in the field of economics. He argued that Popper's falsification appropriateness in the field of economics can be tested by assessment that if falsification approach leads to growth in scientific knowledge. He concluded that it considered a theoretically appropriate general method for the growth of scientific knowledge of economics but it is rarely adopted practically because strict adherence to falsificationism will virtually destroy all the theories of economics. In economics or finance, the complexity of human behavior is simplified in many ontological assumptions that may actually be false such as absolute rational behavior of investors in EMH and CAPM. Economic theories also make assumptions that are practically can not be falsified such as completeness assumption in consumer choice theory.

On ontological level, both PT and EUT differ a great deal but justifying or proving these ontological assumptions using statistical methods are next to impossible. On epistemological level, researchers try to prove assumptions in positivist realm based on statistical application on secondary data from market. Numerous investors invest in stocks based on their beliefs about future outcomes but it is next to impossible to say for certainty whether their beliefs are rational or irrational. Financial models try to prove ontological assumptions via statistical methods that usually infer on correlation, however, correlation does not mean causation. Finally people can be rational or irrational at times. Market prices can be correct or incorrect. Some stocks perform poor than the market index and some perform better, however, different theories explain the reason of out-performance and under-performance differently.

1.6 Overview of Articles

The objective of this thesis is to improve our understanding how measures related to skewness preference and tail risks are priced in the cross-section of stock returns. The the first article reports results is the Norwegian context and the remaining three articles are based on the US market.

1.6.1 Article-1: The MAX Effect in an Oil Exporting Country: The Case of Norway

I write this article together with Thomas Leirvik in which we investigate the effects of investors' lottery-seeking behavior on expected returns in the Norwegian equity market, a relatively small equity market dominated by the energy industry. We use the MAX defined as maximum daily return over the previous month as the proxy of to identify lottery-like stocks. We test whether there is an enthusiasm for lottery like stocks in the Norwegian market such that their demand is at a level to raise their prices higher enough that they have lower expected returns. Despite evidence from recent literature on the significant impact on returns of this factor in other developed European markets, we find that the relationship between the MAX and expected returns is in general insignificant in Norway but it becomes more nuanced when we control for the state of the oil market. The dominance of firms related to the oil industry, which have experienced tremendous growth over the last couple of decades, masks the effect to a large extent. Conditional regressions show that the MAX effect is only significant in the Norwegian stock market when the oil market is in bearish state. These results indicate that investors do not have to forgo expected returns in their pursuance of lottery like stocks during in the long run, however, during the bear state of the oil market the returns on a portfolio of lottery like stocks are significantly lower than the return on a portfolio with lowest lecel of the MAX.

1.6.2 Article-2: Regime Switching Stock Returns and Hybrid Tail Risk

This article is also a joint work of Thomas Leirvik and I in which we investigate the relationship between hybrid tail covariance risk (HTCR) and expected return over the last four decades. Despite a significant positive HTCR-expected return relationship in

Bali et al. (2014), we find that this relationship is not significant at least during average market conditions. We apply a hidden Markov model to identify the prevailing regime in the US market. We find a strong link between market volatility and the relationship between HTCR and expected returns. We analyze this relationship during two market regimes depending on the mean return and return-volatility of the CRSP value weighted market index. We find that these market regimes pose as a catalyst to HTCR pricing in the cross-section of expected returns because HTCR-expected return relationship exists only during the calm regime and it ceases to exist during the noisy regime. Firm level cross-sectional regressions show significant positive relation (no relation) between HTCR and expected returns during calm (noisy) regime even after controlling for other relevant priced factors. We find that HTCR measure correctly predicts the returns during different level of the market downturns but still does not command a risk premium. We find that the US market has become more volatile in the recent years which may be an explanation of HTCR's insignificant relationship with expected returns.

1.6.3 Article-3: ESG and Protection Against Systematic Downside Risks

This article is a solo work in which I investigate the relationship between ESG ratings and the cross-section of expected returns with a lens of systematic downside risk. Employing a novel and large data on ESG ratings for the US market, I find that ESG ratings are not associated with systematic downside risks. I find that a higher rated ESG portfolio is not different in terms of systematic downside risks than that of a lower rated ESG portfolio even though the ratings are quite persistent. A higher rated ESG portfolio is similarly prone to the systematic downside risks as a lower rated ESG portfolio. It can not be ruled out that ESG investing do not provide any benefit in terms of idiosyncratic risks, however, it is evident from asset pricing literature that investors should be concerned about systematic risks because idiosyncratic risks are not rewarded. The results are in line with the imperatives of Fama and French (2007), Cornell and Damodaran (2020) and Cornell (2021) that ESG integration into investment portfolio is more of a taste based investing since it does not provide any benefit in terms of systematic downside risks.

1.6.4 Article-4: Investor Demand and Sustainable Investments

This article is also my solo work in which I analyze risk and return dynamics of sustainable investments with a focus on investor demand. I find that demand for green stocks in comparison with brown stocks is higher and led by active institutional investors especially during the last quinquennium. Predictive regressions show that one standard deviation increase in ESG ratings leads to an increase of 0.3% in the ownership of a stock by active institutional investors in the next quarter. I empirically confirm the theoretical proposition of Pástor et al. (2021) that heightened demand for green stocks leads to better performance of green assets over brown assets. Portfolio analysis and firm level Fama-Macbeth regressions show that green stocks perform better than brown stocks during the period of heightened demand from active institutional investors. Controlling for this demand quashes the performance of green stocks over brown stocks. All the empirical evidence provided in this paper points toward the argument that demand for greener stocks have jumped in the recent years. The higher demand for green stocks versus brown stocks arise due to investors' under-weighting of lowest ESG rated stocks rather than over-weighting highest ESG rated stocks. The percentage of ownership of greener by active institutional investors has been significantly higher in the recent years as compared with the distant past.

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Chapter 2

The MAX Effect in an Oil Exporting Country: The Case of Norway

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The MAX Effect in an Oil Exporting Country: The Case of Norway

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Abstract: This paper assesses the effects of investors' lottery-seeking behavior on expected returns in the Norwegian equity market, a relatively small equity market dominated by the energy industry. We use the MAX factor defined as maximum daily return over the previous month as the proxy of investors' preference for lottery-like stocks. Despite evidence from recent literature that MAX has a negative relationship with the expected returns in other developed European markets, we find that the relationship is generally insignificant in Norway; however, it becomes more nuanced when we control for the state of the oil market. The dominance of firms related to the oil industry, which have experienced tremendous growth over the last couple of decades, masks the effect to a large extent. Conditional regressions show that the MAX effect is only significant in the Norwegian stock market when the oil market is in the bearish state.

Keywords: the MAX effect; oil market; lottery preference; market states; investor sentiment

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1. Introduction

In this paper, we investigate the impact of extreme positive returns over the previous one month on expected returns in an industry-concentrated stock market. The Norwegian market has, in the last three decades, been dominated by energy-related companies in general, and by oil companies, in particular. Thus, the state of the oil market plays an important role in shaping the investors sentiment. Numerous research studies have shown evidence of the relationship between the oil market and the stock market. Park and Ratti (2008) investigated the impact of oil price shock on real stock returns and found that increased volatility in oil prices has a negative effect on real stock returns in the U.S. and most of the European markets. However, an increase in the oil price significantly increases the stock returns in the Norwegian market. Wang et al. (2013) found that the relationship (positive/negative, strength, duration) of oil price movement on aggregate stock returns depends upon whether the country is a net exporter or importer of oil. Ahmadi et al. (2016) showed that the oil price is strongly related to the confidence index. Furthermore, Qadan and Nama (2018) showed that investor sentiments, as measured by augmented proxies of Baker and Wurgler (2006), are strongly related to oil prices and the stock returns of oil companies. However, we, in this paper, use the oil market state as a proxy for investor sentiment, and the results are promising. The maximum daily return over the previous month is termed as the MAX by Bali et al. (2011). The authors found a very strong negative relationship between the MAX and expected returns in the U.S. market. They termed this negative relationship between the MAX and expected returns as the MAX effect. Although the MAX effect is significant in a sample of European markets—see Annaert et al. (2013) and Walkshäusl (2014)—we find no evidence of such an effect in the Norwegian stock market.

We find that the state of the oil market strongly affects the MAX effect in the Norwegian market. Conditional regressions suggest that the MAX effect is significant (insignificant) in the Norwegian stock market when the oil market is in the bearish (bullish) state. It shows that the state of the oil market masks the MAX effect in the Norwegian market. It suggests that the oil market state acts as a barometer of investor sentiment in the Norwegian market. These results are in alignment of the findings of Qadan and Nama (2018), Kumar (2009) and Fong and Toh (2014). We extend the literature by providing empirical evidence of the link between the MAX effect and the oil market in Norway.

Bali et al. (2011) argued that the MAX effect exists because investors, especially retail investors, enthusiastically seek high-MAX/lottery-like-stocks (stocks that experience extreme positive returns), that, in turn, have lower expected returns. We see in the descriptive statistics (Table 1) that high-MAX stocks seem to have higher skewness (1.44) and lower historical monthly average returns (0.53%) than low-MAX stocks (0.51% and 0.82%, respectively). These characteristics make high-MAX stocks lottery-like-stocks, even though portfolio and regression analyses show that the MAX effect is overall insignificant in Norway. However, the MAX effect is significant when the state of the oil market is bearish. It indicates that investors enthusiasm toward lottery-like-stocks increases during the period when the oil market is bearish.

Table 1. The table reports descriptive statistics of high- and low-MAX portfolio stocks. The data are obtained from the TITLON database from January 1996 until December 2016. Portfolios are formed and re-balanced each month on the first trading day based on the maximum daily return in the past one month. All figures are percentages except skewness and avg. stocks/month.

Portfolio	Avg. Stocks/ Month	Mean	Median	Standard Deviation	Skewness	Percentile (1%)	Percentile (25%)	Percentile (75%)	Percentile (99%)
Quartile Portfolio Analysis: 25% stocks in each portfolio									
High MAX	22	0.59	−0.43	16.72	1.47	−39.02	−7.49	7.44	52.89
Low MAX	22	0.66	0.29	10.62	0.56	−26.00	−4.42	5.70	30.94
Tercile Portfolio Analysis: 35% of stocks in high- and low-MAX portfolios and 30% in middle portfolios									
High MAX	30	0.53	−0.31	16.13	1.44	−39.44	−7.15	7.41	49.51
Low MAX	30	0.82	0.40	10.97	0.51	−27.74	−4.47	5.97	32.10

Kumar (2009) explored the demand for lottery-like stocks and found that the preference for lottery-like stocks is more prevalent in individual investors and increases during economic downturns. Fong and Toh (2014) argued that the MAX effect is explained by the behavioral grounds and provided empirical evidence that the MAX effect becomes insignificant after controlling for past sentiments, demonstrating that the effect is a manifestation of the investors' beliefs rather than risk. They found that the effect is significant only when consumer and investor sentiments are high. We principally confirm the findings of Kumar (2009) and Fong and Toh (2014) and find that the MAX effect is significant during the oil market downturns in the Norwegian market. We use the oil market as a proxy for investor sentiments because energy-related companies constitute a major chunk of the Norwegian market and there is evidence of the co-movement of investor sentiment and the crude oil market; see, for example, Zhang and Pei (2019).

We find that the MAX effect is insignificant, and a zero investment portfolio based on it does not guarantee abnormal returns in the Norwegian market. We show that this contrary result is due the concentration of energy-related stocks in the Norwegian market. We find that the MAX effect is significant when the oil market is bearish, and evaporates during a bullish stage in the oil market. We confirm the relationship between the oil market and the Norwegian stock market, which is consistent with the literature of Park and Ratti (2008), Wang et al. (2013), Ahmadi et al. (2016) and Qadan and Nama (2018). However, we also partly confirm the other key result of Bali et al. (2011) that inclusion of IVOL in the regression setting with MAX reverses the puzzling negative relationship between

IVOL and expected returns described by Ang et al. (2006) and Ang et al. (2009). However, we find that the MAX effect does not fully subsume the IVOL effect in the Norwegian market similar to the Chinese market; see Wan (2018). We find that the IVOL-expected returns relationship remains positive and statistically significant in the Norwegian market. However, this relationship is not economically significant in the Norwegian market.

We perform both portfolio and regression analyses to obtain robust results. We also run firm-level Fama and MacBeth (1973) (FM) regressions to control for other firm-specific characteristics, such as firm size (SIZE), book-to-market ratio (BM), idiosyncratic volatility (IVOL), momentum (MOM), illiquidity (ILLIQ), short-term reversal (REV), and CAPM BETA. The results of both portfolio and FM regression analyses suggest that the MAX effect is not significant. We use the Harding and Pagan (2002) method to identify whether the Brent oil market is in a bullish or bearish state. We find that only when the Brent market is bearish, the MAX effect is significantly consistent with Fong and Toh (2014). However, we use the oil market state as the proxy for investor sentiment; Fong and Toh (2014) used the proxies of Baker and Wurgler (2006) for investor sentiment based on the U.S. market data. By doing so, we confirm the link between the Norwegian market and the oil market and show that the oil market plays a consequential role in shaping investor sentiment.

2. Literature Review

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) give financial researchers the mean–variance paradigm. According to the CAPM, the expected return on any security should be equal to the risk-free rate with the addition of a risk premium, which is equal to the security's market beta times the market risk premium. However, the empirical failures of CAPM—see, for example, Friend and Blume (1970), Jensen et al. (1972), Blume and Friend (1973), Fama and MacBeth (1973) and Fama and French (1993)—prompt researchers to look for other approaches to explain expected returns' behavior. Fama and French (1996) introduced two factors in addition to the CAPM market risk factor, SMB and HML. SMB stands for "small minus big" and HML stands for "high minus low". They provided a risk-based justification of these two factors and branded them as proxies for systematic risk. They showed that stocks of small firms outperform stocks of big firms and argue that it is because small firms are more risky due to the additional risk that they face in acquiring resources in comparison with big firms, and small firms are more likely to fail than big firms due to little asset holdings. They also showed that stocks of firms with a high book-to-market value ratio (value stocks) earn higher returns on average than stocks of firms with a low book-to-market value ratio (growth stocks). They argued that it is due to the value stocks being riskier than the growth stocks because the low market value in comparison to assets represents the bad performance or inefficiency of a firm.

The opponents of a risk-based justification—see, for example, Lakonishok et al. (1994), Griffin and Lemmon (2002) and Hirshleifer et al. (2012)—of these two factors claim that this out-performance of small stocks and value stocks over big stocks and growth stocks, respectively, is because of the mispricing of assets. They argued that the out-performance of small stocks over big stocks is because small stocks receive limited analysts' coverage and these small firms' weak fundamentals and non-availability of data make them difficult to price correctly. They termed these factors as anomalies and argued that these factors are discovered through data mining or by generalizing a certain human behavior. There are numerous factors or anomalies in the finance literature that claim to have pricing implications for stocks in the cross section; see, for example, Harvey et al. (2016) and Jensen et al. (2022).

Kane (1982) identified that the higher proportion of wealth invested in risky securities is associated with investors' preference toward higher profits or positive skewness. Tversky and Kahneman (1992) documented this preference for higher gains in their cumulative prospect theory and argued that people often assign more weight to extreme events, as they often prefer a small probability of winning a large prize; they termed the prospect as lottery. Bali et al. (2011) proxied this skewness preference as daily maximum return over the last month—MAX. The MAX factor is based on investors' behavior rather than a risk-based theory. They argued that investors seek stocks that offer very low probability of extreme positive returns in exchange for lower average expected returns. These stocks lie in the right tail of the returns distribution that earn lower average returns and contain some probability of extreme higher returns; these characteristics make them lottery-like stocks.

Walkshäusl (2014) and Annaert et al. (2013) investigated the MAX effect in a sample of European markets and found that it is statistically and economically significant. They argued that the MAX effect is derived from investors' preference toward lottery-like-stocks. Nartea et al. (2014) and Nartea et al. (2017) studied the MAX effect in the Asian emerging markets and found that the relationship between the MAX and expected returns is negative and significant. They argued that this relationship is significant because of the risk-seeking behavior of investors in the Chinese and South Korean markets. Yang and Nguyen (2019) studied skewness preference in the Japanese market and found that investors' preference toward stocks that have positive skewness is significant during bear periods of the market. Cueto et al. (2020) proposed that skewness as well as kurtosis should be added to the CAPM market factor to form a multi-factor asset pricing model. They tested this model on the European stocks and found significant results. We investigate if the MAX effect is prevalent in the Norwegian market and find that it is not significant. This means that investors are not as risk tolerant as in the other European or Asian markets and the preference toward lottery-like-stocks is not at the level that leads to significantly lower expected returns on these stocks.

Kumar (2009) studied the behavior of investors in the U.S. market in the context of lottery demand and found that the demand for lotteries and assets that resemble lottery-like features increases during economic downturns or when the sentiments run high among investors. Motivated by these findings, Fong and Toh (2014) found that if we control for past sentiment in the U.S., then the MAX effect becomes insignificant. It validates the idea that the MAX is a manifestation of investor sentiments. They used investor sentiment index created by Baker and Wurgler (2006); however, there is no such index for the Norwegian market. The Norwegian market is peculiar in a way that, historically, it is claimed to be dominated by energy-related firms. Nevertheless, the widely documented influence of the oil market on the Norwegian stock market by Park and Ratti (2008) and Wang et al. (2013), the relation between oil market and investor sentiment documented by Qadan and Nama (2018) and Song et al. (2019), and the anecdotal history of the Norwegian stock market documented by Von Brasch et al. (2018), Bjørnland (2009) and Cappelen et al. (2014) make the case to control for the oil market state as a proxy for investor sentiment in the Norwegian market.

3. Data

We collect high-quality Norwegian stock data from the TITLON[1] database. TITLON contains financial data for all firms that are, or have been, listed on the Oslo Stock Exchange (OSE). It contains detailed daily, survivorship-bias-free financial data with fully adjusted prices from 1980 until the current year. We define Norwegian stocks as stocks that are traded on the OSE in Norwegian currency and are registered as A shares, ordinary shares, or converted A shares.[2] We collected daily observations of all stocks registered on the OSE from 1980 until 2016. However, we apply data from January 1996 until December 2016[3] to all common Norwegian stocks for two reasons: First, very few stocks were registered on the OSE before 1996, and trading activity was low.[4] Second, the OSE benchmark index was introduced in January 1996. Stocks that are traded for fewer than 10 days in the past one month are treated as missing. We use Norwegian Fama and French (1993) factors data from the Bernt Arne Ødegaard data library.[5] We collect book-to-market ratio data from the Thomson Reuters Datastream.[6] We obtain oil spot prices data from www.eia.gov (accessed on 30 August 2019).

4. Discussion, Analysis and Results

This section presents the analyses performed to scrutinize the relationship between MAX and cross-sectional expected returns. We perform univariate sort portfolio analysis, unconditional Fama–MacBeth cross-sectional regressions and conditional regressions dependent on the state of the oil market.

4.1. Univariate Portfolio Analysis

Compared to the U.S. market, the Norwegian market comprises only a few stocks. Therefore, a decile portfolio analysis would be challenging, as each decile will be left with about 10–15 stocks. Stocks that are priced at less than NOK 10 on the portfolio formation date are also treated as missing due to micro structure noise.[7] Another reason to exclude these low priced and infrequently traded stocks is that Zhang et al. (2018) argued that micro structure noise partly explains the MAX effect. We perform two portfolio analyses: (1) quartile portfolio analysis and (2) tercile portfolio analysis. In the quartile portfolio analysis, each portfolio consists of 25 percent of the stocks available. This means, on average, 22 stocks in one portfolio each month. In the tercile portfolio analysis, high- and low-MAX portfolios contain 34 percent of stocks (30 stocks on average in a month) while the middle portfolio contains 32 percent. Table 1 shows descriptive statistics for both portfolio analyses. It reports the monthly average number of stocks in a portfolio, monthly average/median returns, skewness/standard deviation of monthly average returns, and percentiles of monthly stock returns.

Portfolios are formed and re-balanced each month on the first trading day based on the sort variable MAX. Table 1 shows that high-MAX stocks have lottery-like characteristics; for example, they have, on average, lower mean returns but higher levels of skewness than low-MAX stocks. High-MAX stocks in both quartile and the tercile analyses have a higher level of volatility as well. Percentile values of stock returns are, on average, indicative of lower expected returns and higher volatility and skewness for high-MAX stocks than low-MAX stocks.

We perform both quartile and tercile portfolio analyses. The results of both quartile and tercile portfolio analyses are very similar; however, the tercile analysis is more robust, as each portfolio contains more stocks to damp down individual stocks' idiosyncratic effects. For brevity, however, we only report the results of the tercile portfolio analysis here onwards. Table 2 reports average returns of portfolios sorted on MAX(N), where N represents the average of the N highest daily returns in the past one month. Table 2 further reports mean differences, CAPM-alpha differences, and (Fama and French 1996; Carhart 1997) four-factor alpha differences. Panel A reports the results of equally weighted portfolio analysis, and panel B reports the results of value-weighted portfolio analyses. We use the previous month's market capitalization in the value-weighted portfolio analyses. All the *t-statistics*, estimated by the adjustment of Newey and West (1994), are reported in parentheses.

None of the *t-statistics* in Table 2 are significant, except for the four-factor alpha difference in the equally weighted setting. We cannot claim that the MAX effect is present based only on four-factor alpha differences because the effect is absent in mean return differences and even in CAPM-alpha differences. The absolute values of *t-statistics* are higher in the equally weighted portfolio setting than in the value-weighted portfolio setting. The difference between high-low MAX portfolio has a negative sign in an equally weighted setting; however, the sign is positive in the value-weighted setting. This result is an affirmation that the MAX effect is more likely to be present in small-cap stocks. Most of the big value firms, listed on OSE, are oil-related firms; therefore, it also signals the influence that oil-related firms have on the significance of the MAX effect in the Norwegian market. The average return and CAPM-alpha differences between high- and low-MAX(N) portfolios are mostly negative, but low *t-statistics* compel us to infer that the MAX effect is overall not significant in the Norwegian market.

High-MAX/lottery-like stocks are priced at a premium due to their small probability of producing extreme positive returns. However, if high-MAX stocks do not continue to remain in the high-MAX portfolio, investors would not show enthusiasm for high-MAX stocks in the future, and they would then cease to command a price premium. This lottery-like characteristic of a stock should be persistent to make it a premium-priced stock. We check for this property in high-MAX stocks by examining whether they remain in the high-MAX portfolio in the next month as well. We estimate the month-to-next month transition matrix to find the probability that high-MAX/lottery-like stocks remain in the high-MAX portfolio in the next month or move to another portfolio (middle or low-MAX portfolio).

Table 2. The table reports mean returns on MAX(N)-sorted portfolios and the difference between mean returns and risk-adjusted returns of high- and low-MAX portfolios with the associated Newey and West (1994) adjusted *t-statistics*. We use the Oslo all-share index as the market factor in CAPM and the four-factor model of Fama and French (1996) and Carhart (1997). Three portfolios are formed and re-balanced on the first trading day each month, sorted on MAX(N). All figures are percentages.

	MAX	**MAX(2)**	**MAX(3)**	**MAX(4)**	**MAX(5)**
Panel A: Equal weighted portfolio					
High MAX	0.68	0.60	0.62	0.60	0.66
Middle Portfolio	0.70	0.91	0.91	0.92	0.82
Low MAX	0.93	0.82	0.80	0.82	0.85
Return difference (High-Low)	−0.25	−0.22	−0.18	−0.22	−0.19
(*t-statistic*)	(−0.73)	(−0.61)	(−0.50)	(−0.60)	(−0.52)
CAPM alpha difference	−0.33	−0.32	−0.30	−0.34	−0.32
(*t-statistic*)	(−1.11)	(−1.04)	(−1.01)	(−1.19)	(−1.13)
FF + Carhart alpha difference	−0.59	−0.57	−0.52	−0.52	−0.49
(*t-statistic*)	(−2.31)	(−2.14)	(−2.04)	(−2.17)	(−1.96)
Panel B: Value weighted portfolio					
High MAX	1.09	0.98	0.83	0.66	0.86
Middle Portfolio	0.79	0.91	1.02	1.03	0.87
Low MAX	0.94	0.93	0.97	0.96	0.95
Return difference (High-Low)	0.15	0.04	−0.14	−0.3	−0.09
(*t-statistic*)	(0.38)	(0.11)	(−0.32)	(−0.66)	(−0.18)
CAPM alpha difference	0.00	−0.18	−0.42	−0.61	−0.42
(*t-statistic*)	(0.00)	(−0.47)	(−1.16)	(−1.60)	(−1.08)
FF + Carhart alpha difference	0.00	−0.12	−0.30	−0.42	−0.25
(*t-statistic*)	(0.01)	(−0.30)	(−0.79)	(−1.08)	(−0.61)

Table 3 shows that stocks in a high-MAX (low-MAX) portfolio in a month have a 48.8% (50.5%) probability of staying in the high-MAX (low-MAX) portfolio in the next month. This means that the MAX characteristic is fairly persistent in the Norwegian market. However, the effect is insignificant.[8]

Table 3. This table presents the transition matrix for tercile portfolio analysis. The figures represent the transition probabilities that a stock remains in the same tercile portfolio or switches to another tercile portfolio.

Month (*t*)		**Month (*t* + 1)**	
Portfolio	**High-MAX**	**Middle Portfolio**	**Low-MAX**
High-MAX	0.488	0.308	0.209
Middle Portfolio	0.312	0.352	0.336
Low-MAX	0.199	0.296	0.505

4.2. Fama–MacBeth Regressions

In this section, we examine the cross-sectional relationship between MAX and expected returns at the firm level, using Fama and MacBeth (1973) (FM) regressions, as well as the relationship between MAX and expected returns, controlling for other effects. We follow the traditional FM process, where we run cross-sectional regressions each month where the dependent variable is excess returns and the dependent variables are in three settings. By running these cross-sectional regressions each month, we get the time series of each slope coefficient of the dependent variables. After getting these times series of coefficients, we test that the means of these times series are different from zero. In these tests, we adjust the standard errors using Newey and West (1994) adjustments for possible auto-correlation and heteroscedasticity in the residuals, which leads to robust *t-statistics*. First, we run month-by-month firm-level univariate FM regressions between MAX and expected returns. We then run FM regressions in a bivariate setting by adding one control variable at a time. Lastly, we run month-by-month firm-level full specification FM regressions between MAX and expected returns, simultaneously controlling for BETA, SIZE, BM, MOM, ILLIQ, and REV. Bivariate regressions are important for a deep understanding of the MAX effect because, considering the size of the Norwegian stock market, the MAX effect could conceivably proxy some other effect that can go unnoticed in a full-specification multiple regression.

$$r_{i,t} = \lambda_0 + \sum_{j=1}^{k} \lambda_j X_{i,j,t-1} + \epsilon_{i,t} \tag{1}$$

Equation (1) represents the FM regression setting. Here, $r_{i,t}$ represents the excess return on stock i in month t, the lambdas represent the means of the time series of firm-level cross-sectional regression coefficients, and X represents the lagged explanatory variable of stock i. In a univariate regression setting, $k = 1$ (MAX only); in a bivariate setting, $k = 2$ (MAX and one control variable); and in a full specification setting, $k = 7$ (MAX and all six control variables).

Table 4 provides the standard Fama and MacBeth (1973) test coefficient estimates. We run regressions of the following specification:[9] In a univariate regression setting, the *t-statistic* of the MAX coefficient is just −0.86, which is insignificant though negative. We find a negative relationship between Amihud (2002) illiquidity and expected returns in the Norwegian market, which is puzzling, although this negative relationship is similar to the findings of Annaert et al. (2013) from other European markets. Following these regressions, we reject the existence of a negative relationship between the MAX and expected returns in the Norwegian market.

Table 4. This table reports the lambda coefficients, with the associated Newey and West (1994) adjusted *t-statistics* in parenthesis, of firm-level cross-sectional FM regression results. The first panel reports univariate and bivariate regressions results, and the last row reports results of the full-specification multiple regression. The data are from January 1998 to December 2016.

MAX	BETA	SIZE	BM	MOM	ILLIQ	REV
−0.032						
(−0.86)						
−0.029	0.003					
(−0.76)	(0.70)					
−0.032		0.001				
(−0.86)		(0.99)				
−0.030			−0.000			
(−0.79)			(−0.75)			
−0.026				0.015		
(−0.76)				(3.92)		
0.004					−0.043	
(0.12)					(−3.51)	
−0.045						0.009
(−1.20)						(0.59)
−0.017	0.002	0.0 00	0.000	0.013	−0.031	0.007
(−0.44)	(0.53)	(0.04)	(−0.51)	(3.42)	(−2.40)	(0.48)

4.3. The MAX Effect and Brent Returns

The Norwegian market consists of a limited number of stocks, and is dominated by energy-related firms' stocks; historically, the Norwegian market is highly influenced by oil prices (Park and Ratti 2008; Wang et al. 2013; Wang and Liu 2016). Therefore, it is possible that the common dependence on oil prices produces unexpected results of the MAX effect. For example, if a firm sells oil or oil-related products or services, an increase in oil price leads to higher returns for that firm and, subsequently, to higher returns on the stock of that firm. If oil prices are on the rise (bull phase), a high-MAX stock, which should provide lower returns in the future, may provide higher returns if the firm sells oil or oil-related products or services. Similarly, the magnitude of oil prices/returns increases, and the duration of bull phases may affect the significance of the MAX effect in the Norwegian market because the market is dominated by energy-related firms. Therefore, we investigate the MAX effect separately, first on the whole sample and then conditional on bullish and bearish states of the Brent oil market at the time of investment decision. We split the sample on the basis that at the time $t-1$ of investment the oil market state was bullish or bearish; however, we do not control for the state of the oil market at time t. We run ordinary least square (OLS) regressions, as well as weighted least square (WLS) regressions with market capitalization as the weight, to see the MAX effect corresponding to equally weighted and value-weighted portfolio settings. We use WLS also as a robustness check, as Cochrane (2011) pointed out that OLS puts more weightage on small stocks that are known to be anomalous. Equation (2) represents the regression setting.

$$r_{i,t} = \beta_0 + \sum_{j=1}^{k} \beta_j X_{i,j,t-1} + \epsilon_t | OMS_{t-1} \tag{2}$$

Here, $r_{i,t}$ represents excess returns on stock i in month t, the betas represent the time series coefficients of firm-level OLS and WLS regressions, X represents the lagged explanatory variable of stock i, and OMS_{t-1} is the oil market state during the month $t-1$. We run regressions of Equation (2) in three settings: first, a univariate regression setting, where $k = 1$ (MAX only); second, a bivariate setting, where $k = 2$ (MAX and one control variable); third, a full-specification setting, where $k = 7$ (MAX and all six control variables). We repeat these three regression settings for both equally weighted and value-weighted (OLS and WLS) schemes with three datasets: a full sample and two sub-samples conditional on the oil market state. We use the Harding and Pagan (2002) method to divide the oil market into two states: bullish and bearish.

Table 5 presents the coefficient estimates and associated Newey and West (1994) adjusted *t-statistics* from the regressions of Equation (2). Panel A in Table 5 reports the coefficient estimates and associated Newey and West (1994) adjusted *t-statistics* from (1) univariate regressions—expected returns on MAX; (2) bivariate regressions—expected returns on MAX and one control variable at a time; and (3) full-specification multiple regressions—expected returns on MAX, controlling for BETA, SIZE, BM, MOM, ILLIQ, and REV, where the regression type is OLS, meaning that all returns are equally weighted throughout the chosen dataset (full sample (250 months of data) in panel A1, sub-sample when the oil market was bullish (115 months of data) in panel A2, and sub-sample when the oil market was bearish (135 months of data) in panel A3). The same results are reported in panel B of Table 5, but the regression type is WLS, meaning that all returns are weighted according to the market capitalization of the previous month throughout the chosen dataset.

Table 5. This table reports the beta coefficients, with the associated Newey and West (1994) adjusted *t-statistics* in parentheses of firm-level OSL and WLS regression results. Panel A (Panel B) reports OLS (WLS) coefficient estimates of univariate, bivariate and full-specification multiple regressions, first for the whole sample, second for time periods when the oil market is bullish at the time of investment decision, and third for time periods when the oil market is bearish at the time of investment decision. The data are from January 1998 to December 2016.

Panel A: Equal-Weighted/OLS																				
A1: All Sample							**A2: Bullish Oil Market**							**A3: Bearish Oil Market**						
MAX	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**	**MAX**	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**	**MAX**	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**
−0.068							−0.041							−0.134						
(−1.22)							(−0.54)							(−2.07)						
−0.059	−0.007						−0.046	0.004						−0.115	−0.014					
(−1.10)	(−1.41)						(−0.60)	(0.52)						(−1.88)	(−2.82)					
−0.064		0.000					−0.024		0.002					−0.135		0.000				
(−1.10)		(0.39)					(−0.29)		(0.98)					(−2.05)		(−0.14)				
−0.068			0.000				−0.041			0.000				−0.134			0.000			
(−1.72)			(0.09)				(−0.73)			(0.03)				(−3.30)			(0.04)			
−0.056				0.016			−0.007				0.022			−0.136				0.018		
(−1.04)				(2.80)			(−0.10)				(2.91)			(−2.21)				(2.80)		
−0.037					−0.035		0.011					−0.049		−0.116					−0.023	
(−0.72)					(−3.93)		(0.15)					(−3.89)		(−1.92)					(−1.98)	
−0.115						0.089	−0.077						0.084	−0.206						0.111
(−2.04)						(3.74)	(−1.05)						(2.86)	(−3.04)						(3.80)
−0.082	−0.006	−0.001	0.000	0.014	−0.024	0.080	−0.014	0.004	−0.001	0.000	0.019	−0.036	0.069	−0.191	−0.013	−0.001	0.000	0.017	−0.013	0.105
(−1.36)	(−1.16)	(−0.91)	(0.00)	(2.42)	(−2.76)	(3.27)	(−0.16)	(0.51)	(−0.27)	(−0.07)	(2.40)	(−2.70)	(2.16)	(−2.74)	(−2.55)	(−1.06)	(−0.03)	(2.68)	(−1.13)	(3.63)
Panel B: Value-Weighted/WLS																				
B1: All Sample							**B2: Bullish Oil Market**							**B3: Bearish Oil Market**						
MAX	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**	**MAX**	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**	**MAX**	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**
−0.088							0.038							−0.239						
(−0.81)							(0.22)							(−2.15)						
−0.069	−0.012						0.050	−0.008						−0.219	−0.012					
(−0.67)	(−1.47)						(0.30)	(−0.56)						(−2.03)	(−1.26)					
−0.076		0.001					0.072		0.002					−0.228		0.001				
(−0.71)		(0.69)					(0.42)		(1.22)					(−2.08)		(0.51)				
−0.088			0.000				0.038			0.000				−0.239			0.000			
(−1.09)			(−0.08)				(0.30)			(0.08)				(−2.47)			(−0.59)			
−0.088				0.004			0.063				0.015			−0.249				0.008		
(−0.88)				(0.46)			(0.42)				(1.34)			(−2.29)				(0.90)		
−0.083					−0.041		0.047					−0.060		−0.236					−0.032	
(−0.75)					(−3.15)		(0.27)					(−2.65)		(−2.11)					(−2.11)	
−0.113						0.054	0.030						0.027	−0.304						0.107
(−1.03)						(1.61)	(0.17)						(0.62)	(−2.76)						(2.65)
−0.074	−0.012	0.001	0.000	0.003	−0.033	0.050	0.117	−0.011	0.003	0.000	0.016	−0.043	0.022	−0.281	−0.011	0.001	0.000	0.008	−0.017	0.103
(−0.63)	(−1.51)	(0.78)	(0.10)	(0.44)	(−2.35)	(1.49)	(0.64)	(−0.80)	(1.32)	(0.23)	(1.38)	(−1.86)	(0.52)	(−2.37)	(−1.21)	(0.43)	(−0.33)	(0.86)	(−1.07)	(2.58)

The MAX effect is significant only when the oil market is bearish, producing *t-statistics* of −2.07 in equal-weighted and −2.15 in value-weighted univariate regression settings. The MAX effect also survives the addition of control variables BETA, SIZE, BM, MOM, ILLIQ, and REV, producing *t-statistics* of −2.74 in equally weighted and −2.37 in value-weighted full-specification regression settings. The MAX effect is not significant in full samples and sub-samples when the oil market is bullish. The insignificant MAX effect in panel A2 and the positive sign of the MAX relationship in panel B2 hint at the oil market influence on the Norwegian stock market. With MAX being a valid proxy of lottery-like-stocks, the results from panel A3 and B3 may be interpreted as increased investor enthusiasm for lottery-like stocks during downturns in the oil market. This increased demand for lottery-like stocks happens during the time when the oil market is bearish, which leads to the significant negative relation between the MAX and expected returns; however, there is no relation if, at the time of investment decision, the oil market is bullish. The oil market can be viewed as a proxy of investor sentiments considering the concentration of energy-related stocks in the Norwegian market.

Figure 1 illustrates the Brent price in the spot market and its monthly return averages. The grey color in the background of Figure 1 represents bearish periods. The grey and white colors in the background switch very frequently and after very short spans of time because the method of Harding and Pagan (2002) to determine market phases allows a minimum phase of two months. The thinnest grey or white background color represents two months at the minimum. Figure 1 clearly shows that prices and returns are on the rise in the white regions and are declining in the grey regions. The average monthly returns on Brent during the bearish and bullish phases are −1.83% and 4.96%, respectively. The longest bear (bull) phase in the Brent market is 13 months long, from November 2013 to December 2014 (May 1999 to January 2000). Table 6 presents descriptive statistics of the bull and bear periods of Brent. Mean returns in the bear (bull) periods are negative (positive), and the standard deviation is slightly higher in the bear periods than the bull periods.[10]

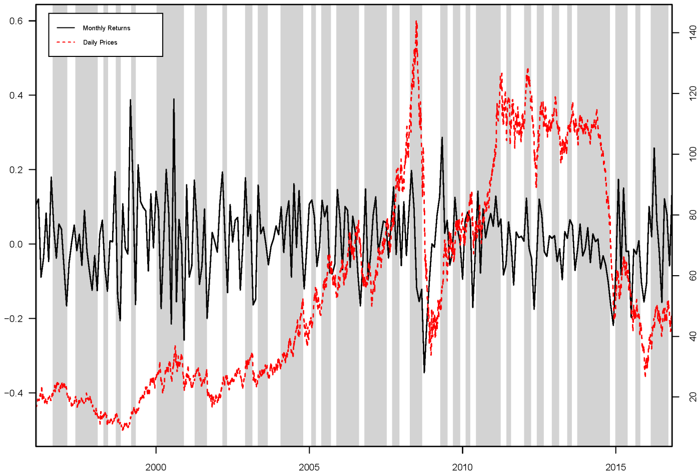

Figure 1. Brent price and monthly return averages.

Table 6. This table presents some descriptive statistics of bull and bear states of Brent. All figures are percentages.

Statistic	Bear Periods		Bull Periods	
	Monthly Values	Annualized Values	Monthly Values	Annualized Values
Mean Return	−1.83	−24.34	4.96	78.71
Median Return	−1.96	−26.27	3.24	46.66
Standard Deviation	10.46	36.23	9.59	33.23
Minimum Return	−34.57	-	−21.12	-
Maximum Return	39.03	-	38.78	-

4.4. The MAX Effect and Idiosyncratic Volatility

We use Equation (2) to investigate the relationship between the MAX, MIN (minimum daily return in past one month) and IVOL in the Norwegian market.[11] We run these regressions for the equally weighted setting and the value-weighted setting using the sub-sample when the oil market is bearish. We use this sub-sample because the MAX effect is present only in the bearish state of the oil market. Table 7 presents the beta coefficients and associated Newey and West (1994) adjusted *t-statistics* of these regressions.

Table 7. This table reports the beta coefficients, with the associated Newey and West (1994) adjusted *t-statistics* in parenthesis, of firm-level OSL and WLS regressions. The dataset comprises time periods between 1998 and 2016 when the Brent oil market was bearish.

Panel A: Equal-Weighted/OLS								
IVOL	**MAX**	**MIN**	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**
−0.007								
(−3.20)								
0.004	−0.127							
(2.52)	(−1.93)							
0.004	−0.126	0.288						
(2.47)	(−1.95)	(3.23)						
0.005	−0.200	0.095	−0.014	−0.003	0.000	0.017	−0.005	0.098
(3.60)	(−2.91)	(1.32)	(−2.68)	(−2.49)	(−0.10)	(2.68)	(−0.43)	(3.48)
Panel B: Value-Weighted/WLS								
IVOL	**MAX**	**MIN**	**BETA**	**SIZE**	**BM**	**MOM**	**ILLIQ**	**REV**
−0.011								
(−3.36)								
0.002	−0.244							
(0.93)	(−2.31)							
0.003	−0.265	0.288						
(1.22)	(−2.64)	(3.23)						
0.005	−0.330	0.267	−0.010	−0.002	0.000	0.010	0.000	0.075
(1.86)	(−2.76)	(1.89)	(−1.01)	(−1.03)	(−0.21)	(1.09)	(−0.02)	(1.74)

In panel A of Table 7, IVOL has a negative and significant relationship with the expected returns. However, similar to Bali et al. (2011), adding MAX to the regression (third and fourth rows of Table 7) reverses the sign of the relationship. In Panel A, MAX remains significant at 10 percent with IVOL as a control variable and at 5 percent with IVOL and MIN as control variables. The MAX effect remains highly significant in value-weighted regression settings. However, IVOL loses its significance in value-weighted settings. We see in Table 7) panel A that the MAX does not fully subsume IVOL; IVOL remains statistically significant but the relationship is positive with expected returns.

5. Conclusions

The empirical results show that MAX is not significant in the Norwegian market, owing to the strong association between the Norwegian market and the oil market. However, when we control for different states of the oil market, the MAX effect seems to appear only in bearish periods of the oil market. Oil market states can be viewed as a proxy of investor sentiments for the Norwegian stock market and this result has implication for other oil exporting countries' markets. Our results are in line with the findings of Kumar (2009) and Fong and Toh (2014) that the investors' tendency to seek lottery-like stocks increases during adverse economic conditions and when the investor sentiments are high. Our results are consequential in the sense that most of the small equity markets are usually influenced by one or a couple of industrial sectors or commodity markets. Therefore, controlling for these specific influence factors could open new doors for further research. Our results are relevant for other oil exporting countries, such as Canada and Saudi Arabia, because a bullish (bearish) oil market is good (bad) news for these countries similar to Norway. These results imply that an investment strategy based on the MAX factor (long on low-MAX stocks and short on high-MAX stocks) does not produce positive returns in the Norwegian market at least during normal market conditions. Investors need to adjust the influence of the oil market in the Norwegian market to conduct a successful investment strategy based on the MAX factor. The limitations of the findings are that the Norwegian market is changing, with investments going into firms other than those that are oil related. It means a lower percentage of capital out of the total Norwegian market capitalization in oil-related firms in the future, which will decrease the influence of the oil market on the Norwegian stock market. Another limitation on the exploitation of the investment strategy based on the MAX is that it is difficult to short high-MAX stocks because they are relatively illiquid and small. Moreover, we partly confirm the findings of Bali et al. (2011) that controlling for MAX reverses the negative relationship between IVOL and expected returns; however, IVOL remains significant in the Norwegian market.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Variables Definitions

MAX(N):

$$MAX(N)_{i,t} = \frac{\sum_{(N=1)}^{N} MAX(R_{i,N})}{N} \tag{A1}$$

where $R_{i,N}$ is the daily return on stock i and N represent number of highest daily returns selected.

IVOL: To estimate the individual idiosyncratic volatility of an individual stock, we use the same definition as in Bali et al. (2011), where the return generating process is

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \epsilon_{i,d} \tag{A2}$$

where $\epsilon_{i,d}$ is the idiosyncratic return on day d. The idiosyncratic volatility of stock i in month t is defined as the standard deviation of daily residuals in month t.

$$IVOL_{i,t} = \sqrt{var(\epsilon_{i,d})} \tag{A3}$$

ILLIQ: Following Amihud (2002), we measure stock illiquidity for each stock in month t as the ratio of the absolute monthly stock return to its NOK trading volume

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{Volume(NOK)_{i,t}} \tag{A4}$$

where $R_{i,t}$ is the return on stock i in month t and $Volumn(NOK)_{i,t}$ is the respective monthly trading volume in NOK divided by NOK 100 million.

SIZE: SIZE is natural log of average market capitalization of stock i during the month $t-1$.

REV: REV of stock i is the return on stock i on month $t-1$.

BETA: We use the same definition as in Bali et al. (2011) did. We follow Scholes and Williams (1977) and Dimson (1979) to measure beta.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_1(R_{m,d-1} - r_{f,d-1}) + \beta_2(R_{m,d} - r_{f,d}) + \beta_3(R_{m,d+1} - r_{f,d+1}) + \epsilon_{i,d} \tag{A5}$$

To measure market beta, we run this regression each month and extract beta coefficients β_1, β_2 and β_3 and then take their average.

$$\beta_i = \frac{\beta_1 + \beta_2 + \beta_3}{3} \tag{A6}$$

Appendix B

Table A1. Number of common stocks registered at OSE over the years.

Year	Total Common Stocks Registered at OSE	Total Norwegian Common Stocks
1980	78	78
1981	85	85
1982	91	91
1983	97	97
1984	111	111
1985	124	124
1986	131	131
1987	128	128
1988	126	126
1989	126	126
1990	135	134
1991	122	120
1992	123	121
1993	138	132
1994	144	135
1995	159	148
1996	172	160
1997	214	192
1998	231	203
1999	228	202
2000	226	197
2001	210	179
2002	196	167
2003	190	164
2004	183	156
2005	217	184
2006	238	197
2007	272	217
2008	266	211
2009	247	191
2010	238	184
2011	231	177
2012	221	174
2013	220	171
2014	216	167
2015	208	158
2016	198	153

Table A2. Bull and bear phases and monthly return averages of Brent oil.

Start	End	Phase	Monthly Average Return
January 1996	August 1996	Bull	4.53
September 1996	February 1997	Bear	−2.17
March 1997	May 1997	Bull	0.21
June 1997	February 1998	Bear	−3.71
March 1998	April 1998	Bull	4.52
May 1998	June 1998	Bear	−9.55
July 1998	September 1998	Bull	6.97
October 1998	November 1998	Bear	−17.32
December 1998	March 1999	Bull	11.44
April 1999	May 1999	Bear	0.02
June 1999	January 2000	Bull	8.86
February 2000	December 2000	Bear	0.28
January 2001	April 2001	Bull	4.60
May 2001	September 2001	Bear	−4.31
October 2001	March 2002	Bull	3.87
April 2002	May 2002	Bear	−5.35
June 2002	December 2002	Bull	4.29
January 2003	March 2003	Bear	−2.12
April 2003	May 2003	Bull	0.50
June 2003	September 2003	Bear	0.45
October 2003	February 2004	Bull	3.63
March 2004	November 2004	Bear	2.82
December 2004	February 2005	Bull	7.17
March 2005	April 2005	Bear	0.63
May 2005	June 2005	Bull	5.47
July 2005	October 2005	Bear	0.48
November 2005	December 2005	Bull	4.64
January 2006	September 2006	Bear	−0.09
October 2006	November 2006	Bull	5.36
December 2006	August 2007	Bear	1.74
September 2007	October 2007	Bull	10.45
November 2007	January 2008	Bear	0.63
February 2008	May 2008	Bull	9.20
June 2008	October 2008	Bear	−12.89
November 2008	May 2009	Bull	2.50
June 2009	August 2009	Bear	1.21
September 2009	October 2009	Bull	5.08
November 2009	January 2010	Bear	−1.62
February 2010	March 2010	Bull	7.45
April 2010	May 2010	Bear	−5.22
June 2010	July 2010	Bull	6.19
August 2010	May 2011	Bear	3.77
June 2011	July 2011	Bull	0.26
August 2011	September 2011	Bear	−5.48
October 2011	February 2012	Bull	4.03
March 2012	May 2012	Bear	−7.49
June 2012	July 2012	Bull	4.34
August 2012	October 2012	Bear	0.76
November 2012	January 2013	Bull	2.01
February 2013	April 2013	Bear	−5.17
May 2013	July 2013	Bull	3.81
August 2013	September 2013	Bear	−1.01
October 2013	November 2013	Bull	1.98
December 2013	December 2014	Bear	−4.95
January 2015	February 2015	Bull	5.42
March 2015	July 2015	Bear	−3.36
August 2015	October 2015	Bull	−1.06
November 2015	December 2015	Bear	−12.94
January 2016	April 2016	Bull	6.82
May 2016	December 2016	Bear	2.41

Notes

1. TITLON contains financial data from 1980 until present, for further details, see https://titlon.uit.no/ (accessed on 11 January 2018).
2. They are categorized as "A-aksjer", "Ordinære aksjer", and "Konverterte A" in the TITLON database.

3 We also performed all analyses on datasets for different periods—1982–2016, 1985–2016, and 1990–2016, for example; however, the results were similar to those for the 1996–2016 dataset. For brevity, therefore, we report most results for the 1996–2016 data.

4 Table A1 in Appendix B reports the number of stocks registered on the OSE over the years.

5 http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html (accessed on 7 November 2018).

6 Book-to-market data before 1998 are rarely available for all firms. Therefore, we report results for 1998–2016 data where book-to-market-characteristic data are involved.

7 Even if we include these stocks, the results remain similar.

8 A minimum transition probability of 33.3% is required in tercile portfolio analysis to show persistence.

9 As Bali et al. (2011) did in their paper, we also winsorize the right-hand-side variables at the 0.5 % and 99.5% levels before running all regressions.

10 Duration of bull and bear periods are presented in detail in Table A2.

11 Following Bali et al. (2011), we orthogonalize IVOL with respect to MAX and MIN when we use any two of these three variables in regressions to avoid the multicollinearity problem. MAX-IVOL and MIN-IVOL are 88% and 82% correlated, respectively, in the Norwegian market.

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Tails of Returns' Distribution and Expected Returns: An Empirical Study

The classical literature of finance assumes investors as rational decision makers who maximize their wealth by conforming to the axioms of expected utility theory. It means that investors utility from a risky investment is equal to the expected utility which is estimated by weighting each outcome's utility by its probability. However, empirical findings from financial markets suggest that the expected utility theory as a descriptive theory of investors' decision making under risk may not hold true all the time. The prospect theory of decision making under risk suggests that investors tend to overweight their dislike of extreme negative outcomes. They often tend to prefer extreme positive outcomes with a small possibility over a normal outcome.

Deriving the motivation from these postulates, this thesis investigates investors preference towards positive returns in the Norwegian stock market. It also investigates the pricing of left tail risk in the US stock market. Firms that perform better on environmental, social and governance (ESG) aspect are marketed as investment prospects with lower tail risks. This thesis contributes to the understanding of tail risks associated with ESG investments. It further investigates the expected returns and the demand for ESG investments.

The study comprises of four articles. The first two articles apply different methods to identify market states and the repercussions of these states on the returns of investors seeking extreme positive returns and investors that take higher tail risk. The results from the articles suggest that both these phenomena exist, however, during some particular market states. The last two articles investigate ESG investments with respect to tail risks and investor demand and the results show that the demand of ESG investments is high and increased in recent years and the ESG investments do not protect investors from tail risks.

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