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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]

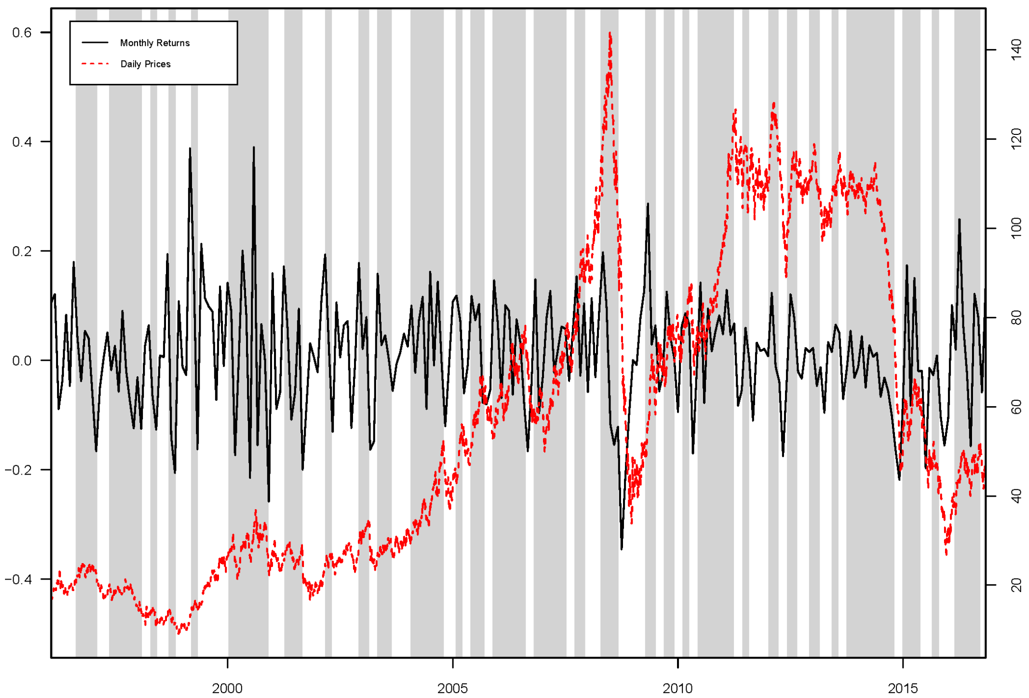

Figure 1. Brent price and monthly return averages.

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

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

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.

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

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.

$$\beta_i = \frac{\beta_1 + \beta_2 + \beta_3}{3} \quad \text{(A6)}$$

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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