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Comovement in the Norwegian Stock Market

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Abstract

We present the first comprehensive study of excess comovement in the Norwegian stock market, and find that stocks on the OBX index in Norway comove more than their fundamentals would suggest. The comovement is increasing over time, and of large economic magnitude after 2009. Between 2009 and 2018, our results indicate that 14% of the variance of OBX stocks stems from excess comovement. The OBX bases membership on volume traded, unlike previously researched indexes, which base membership on market capitalisation. Critics have suggested that index structure is the cause of previously found excess comovement, but our findings show that excess comovement exists even on differently structured indexes. Our findings therefore present new evidence in support of index membership causing excess comovement.

Acknowledgements

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Contents

1 Research problem and motivation

A large amount of research indicates that the prices of assets comove more than their fundamentals would suggest. This comovement is seen for equities within several countries, including the US (Ambrose, Lee, & Peek, 2007; Barberis, Shleifer, & Wurgler, 2005; Kallberg & Pasquariello, 2008; Vijh, 1994), the UK (Claessens & Yafeh, 2012; Mase, 2008), and Japan (R. M. Greenwood & Sosner, 2007; Suzuki et al., 2015). Research also suggests increased comovement between different asset classes that were previously unrelated, such as equities and commodities (Basak & Pavlova, 2016; Pindyck & Rotemberg, 1988; Tang & Xiong, 2012). Both stocks and commodities are in other words claimed to be affected by comovement factors that are independent of the fundamentals of the underlying asset. This excess comovement is in violation of the concept that stock prices only reflect the fundamental value of a given firm (Samuelson et al., 1965; Ross, 1976). The study of excess comovement is therefore a crucial aspect of asset pricing (Kallberg & Pasquariello, 2008).

Potential consequences of comovement in excess of fundamentals include increased volatility (Basak & Pavlova, 2013; Tang & Xiong, 2012), increased financial instability (Wurgler, 2010) and reduced possibilities of diversification (Rua & Nunes, 2009). Understanding both the magnitude of comovement effects, and their cause, is therefore of significance to investors, risk managers, government agencies, and academics.

Excess comovement is commonly defined as covariance between asset returns that is not explained by fundamentals. One of the most common ways to investigate excess comovement for stocks is through studying index inclusions. Being included in an index is generally believed to be an information-free event, meaning that the stock is fundamentally unchanged from joining the index. If joining the index is truly information-free, then increased comovement after index inclusion, must be solely due to the inclusion. The index inclusion thereby works as a natural experiment (Ambrose et al., 2007).

The majority of the comovement literature has claimed to find excess comovement in indexes by performing such experiments. In the US, UK and Japan, the economic magnitudes of the findings are high, with some studies indicating that excess comovement accounts for 20 to 40 percent of the total variation on the S&P 500, FTSE 100, and Nikkei 225 indexes (Barberis et al., 2005; Mase, 2008; R. M. Greenwood & Sosner, 2007). Comovement has not been studied comprehensively in Norway before, and we therefore raise the question: is there excess comovement in the Norwegian stock market?

Recently, there has been more doubt about whether the findings of the major comovement studies are correct. Chen, Singal, and Whitelaw (2016), von Drathen (2014) and Kasch and Sarkar (2012) claim that the assumption that index inclusion is an information-free event is incorrect – inclusions to both the S&P 500 and the FTSE 100 have substantial changes in fundamentals around the inclusion date. They pose that these changes in fundamentals are what drive the majority of the change in comovement, not the index inclusion. For instance, since the S&P 500 index bases membership on stock market capitalisation, any stock that joins is likely a momentum stock – one that has performed well prior to inclusion. Moreover, index comovement is almost exclusively restricted to indexes which base inclusion on market capitalisation.

We fill a gap in this literature by examining index inclusion events for which market capitalisation is not a criteria. Specifically, we study index comovement on the OBX index in Norway, which crucially bases membership on how much the stocks are traded, consisting of the top 25 most traded stocks on the Oslo Stock Exchange.

To our knowledge, this is the first study to examine comovement on such an index. As the construction of the index is different from that of previous studies, we can examine comovement in a new light.

Critics of the excess comovement literature claim that the changes in fundamentals that apply to all stocks joining the S&P 500 index and FTSE 100 index are due to the construction of these indexes. OBX, however, is constructed on a different set of eligibility criteria and thus, the same traits do not apply to stocks joining the OBX index. Inclusions to the OBX are exposed to a potentially different set of changes in fundamentals.

We create a model which clearly defines all the assumptions necessary for the standard comovement test to accurately identify excess comovement. We then run the standard comovement test as a baseline analysis, and find indications that there is excess comovement on the OBX index. The excess comovement has risen sharply over time, and for the 2009-2018 period, it is equal to approximately 22% of the variance of the OBX. This is a similar magnitude to what Barberis et al. (2005) found in the S&P 500 for 1988 to 2000.

We perform several tests to determine whether stock inclusion into the OBX is an information-free event. We extend the single-factor model to include the Carhart 4-factor model, test for non-synchronous trading effects, test for momentum's relation with comovement, and examine the effects of industry trends. None of these explain the excess comovement, but we find that a previously unexamined variable in comovement literature does: volume traded. All inclusions to the OBX have increased volume traded both before and after inclusion into the OBX, and increased volume traded causes increased comovement with the OBX. This fact causes the single-factor model to overestimate the excess comovement.

To control for volume traded, we perform a matched samples approach, where we match inclusions with sample stocks that see similar changes in volume traded. We find that approximately a third of the excess comovement suggested by the single-factor model was due to the increase in volume traded. After controlling for the effects of volume traded, approximately 14% of the variance of the OBX index is a result of comovement in excess of what fundamentals would suggest. We verify this result by employing a regression discontinuity design using an instrumental variable, and find similar estimates for excess comovement.

We also check the robustness of our findings by examining stocks which were deleted from the OBX index. We repeat our tests, and find that these stocks display a similar decrease in comovement as the index inclusions saw an increase.

Our research makes three main contributions. The first is aimed at the Norwegian stock market, while the second and third are interesting for a broader international audience. Firstly, as no other paper has thoroughly examined index comovement in Norway before, our results bring new insight about which factors affect the Norwegian stock market. Stocks included in the OBX index see increased comovement, and as a result, also increased volatility. We also find that volume traded is a significant factor for how much stocks comove in Norway.

Secondly, while previous research has primarily studied and discussed comovement in large indexes which base inclusion on market capitalisation, we find that there is also excess comovement in a smaller index with a different inclusion criteria.

Thirdly, we also find that despite the difference in index inclusion criteria, the index's specific construction also affects which factors affect stock comovement.

This paper is constructed as follows: Section 2 presents an overview of the major literature on comovement. Section 3 presents some brief exploratory data on the OBX index. In Section 4 we create the model for the most used comovement test, and present the results of that test. Section 5 consists of an analysis of whether the assumptions of the model truly hold, by various tests for momentum, firm size, industry membership, proxies for fundamentals and volume traded. In Section 6 we create matched samples based on the findings of Section 5, and use these matched samples to estimate excess comovement after controlling for changes in fundamentals. Section 7 consists of regression discontinuity design using an instrumental variable, to further establish causality. In Section 8, we perform several robustness tests to ensure the robustness of our results. Section 9 presents a discussion on our findings and their main implications. Finally, we conclude in Section 10.

2 Literature review

There are two main perspectives in the comovement literature (Barberis et al., 2005). The first is that all comovement stems from fundamentals, meaning correlated changes in the fundamental values of firms. The second perspective claims that comovement is also driven by non-fundamental sources. The latter entails that some groups of stocks comove in excess of what their fundamentals would suggest. This is known as excess comovement. It is necessary to understand both sources of comovement, in order to be able to prove whether there is excess comovement in the Norwegian Stock market. This section is organised as follows: we first give a short introduction to the fundamental theory of comovement. Afterwards, we review the literature of non-fundamental comovement related to our thesis question. Lastly, we review the findings and literature of comovement in stock indexes.

2.1 Fundamental comovement

In the fundamental view of comovement, asset prices only comove due to correlated changes in cash flows or common variation in discount factors (Coakley, Kougoulis, et al., 2004). This view is based on classical finance models such as the efficient market hypothesis, which is one of the most established pieces in financial theory (Fama, 1970; Samuelson et al., 1965). The efficient market hypothesis assumes rational investors who price assets based on expectancy about future cash flows. If a stock price changes, the reason is that investors' expectations of future cash flows have changed. This fundamental view is also a cornerstone in arbitrage pricing theory, where any deviation from a fundamental price will be adjusted by arbitrage investors (Ross, 1976).

2.2 Breaches from fundamental comovement

Fundamental theories explain a large part of price comovement, but there exists a fair share of empirical evidence in favour of excess comovement for several asset classes. One early example is Pindyck and Rotemberg (1988). They attempted to explain commodity comovement by macroeconomic variables, but the commodities comoved far more than any set of macroeconomic variables could explain. Either there is some unknown macroeconomic variable that affects commodity comovement, or actors in commodity markets react to non-economic factors. Examining the latter would later turn into a sizeable research field about how investor behaviour affects comovement.

In the middle and late 1990s, Bodurtha Jr, Kim, and Lee (1995) and Froot and Dabora (1999) found that certain groups of stocks comoved more than their fundamentals would suggest. Bodurtha Jr et al. (1995) studied US closed-end funds that held foreign assets, and found that the price of those funds did not always match the net asset value of the fund – the fund would occasionally trade at a premium or a discount compared to the values of the assets the firm owned. The researchers found that the reason for the mispricing was that the closed-end funds comoved more with the US stock market, than with the foreign stocks which the funds owned. This, they posed, meant that the US closed-end funds, which owned only foreign stocks, were exposed to US-specific risk. Further, that this US-specific risk stemmed not from fundamentals, but from investor sentiment.

Froot and Dabora (1999) reach the same conclusion by studying Siamese-twin stocks – stocks which are traded on several stock exchanges, but have claims to the exact same cash-flow. By fundamental theory, two stocks with claims to the exact same cash flow should have the exact same price, but that was not the case for the Siamese-twin stocks. They displayed excess comovement with stocks in the countries where they were traded most. Froot and Dabora (1999) posed that a plausible explanation for these findings was that there are country-specific sentiment shocks.

An interesting takeaway from these papers, is that there are strong signs that assets comove not only due to shocks to the demand of the owners of the assets. Shocks which are unrelated to the actual fundamentals of the stocks, and change the owners' demand for the stocks. These demand shocks cause all the stocks affected by the demand changes to comove in excess of fundamentals. A closely related branch of literature, is the literature of international contagion in financial markets. The part of this literature that is relevant for our thesis, is focused on how a negative shock to asset prices in one country, can cause negative shocks in other countries which were not directly hit by the original shock.

One strong example of international contagion was the "Russian virus" of 1998

(Baig & Goldfajn, 2001; Calvo, 2004). In August 1998, Russia defaulted on parts of its public debt. This caused crises in asset markets in several countries, including South American countries which had no economic ties to Russia. Baig and Goldfajn (2001) pose that the Russian crisis caused a panic among international investors which caused a crisis in Brazil. He presents evidence that the Russian debt default caused international investors to withdraw their money from Brazil, and that this resulted in a large drop in asset prices. Calvo (2004) finds that that the contagion was at least partly caused by leveraged institutional investors on Wall Street. These investors were specialists in investing in emerging markets, and were therefore invested in both Russia and Brazil. The losses in Russia forced the investors to sell their other assets in emerging markets to pay margin calls. This then caused selling pressure on Brazil. This is a clear example that stocks which have similar investors, may see excess comovement, since shocks that affect the investors will affect all the stocks that those investors own.

2.3 Comovement with stock indexes

The previous section argues that there exists evidence that comovement is not driven entirely by fundamentals, but also non-fundamental factors. One cause of non-fundamental comovement may be demand effects caused by shocks to the owners of the stocks. Testing for whether one group of assets comoves more than fundamentals suggest is generally difficult, since there are a variety of factors that cause assets to comove. One of the most established ways to test for excess comovement is through examining stocks which are included in an index. The idea behind examining index inclusions, is that index inclusion itself should bring no news about the fundamentals about the stock. If that is correct, then a stock comoving more with an index after joining it, can be considered as proof of non-fundamental comovement (Cathcart, El-Jahel, Evans, & Shi, 2019).

Vijh (1994) was one of the first to look at excess comovement from index inclusion. He employed a test on the S&P 500 which would become the standard test of index comovement. He calculated the beta of each inclusion for the 250 days before index inclusion, and the 250 days after index inclusion, using the market model to calculate the betas. The results were that after inclusion in the index, the betas increased.

Vijh (1994) attributed this to investors using trading strategies which involve buying or selling the entire index at the same time.

Barberis et al. (2005) build on the work of Vijh (1994), and investigate excess comovement in the S&P 500 from 1967 to 2000. They asses beta changes for stock inclusions to, and deletions from, the S&P 500 index. They find that when a stock is included in the S&P 500 index, its R^2 and beta with respect to the S&P 500 index increase, while the opposite happens when a stock is excluded. The other major contribution of Barberis et al. (2005) is their two views of what causes excess comovement: Category-based comovement and habitat based comovement. Category based comovement occurs when investors classify different securities into the same asset class, and shift resources in and out of this class in a correlated way. Habitat based comovement occurs when investors as a group limit the transactions to a given set of securities, and interchange in and out of that set in tandem. These two explanations have in the aftermath of the study been gathered as demand effects (R. Greenwood, 2008). They have received support in several papers that have studied comovement (Ambrose et al., 2007; Green & Hwang, 2009). To further control for fundamental changes, Barberis et al. (2005) employ a matched sample test. They match firms with regards to size and industry, and test whether the matched sample displays similar changes in comovement as the included stocks. They find that this kind of change does not appear, and therefore reject the fundamental view of comovement and attribute the excess comovement mainly to demand effects.

This way of testing comovement has received some criticism. Chen et al. (2016) challenge the results of Barberis et al. (2005), and claim that the reason betas increase after index inclusion, is not that they joined the index, but rather that the firms have fundamentally changed. Since the S&P 500 consists of the stocks with the highest market value, stocks that join the S&P 500 have necessarily increased in market value prior to joining. This means that they are all high momentum stocks. Chen et al. (2016) create matching samples which match on both firm size and momentum. These matched samples exhibit almost as large an increase in the betas as the actual inclusion into the S&P 500 did, and Chen et al. (2016) therefore conclude that the increase in beta stems from the inclusions being momentum stocks, rather than from excess comovement.

Kasch and Sarkar (2012) also question whether there truly is a non-fundamental effect for S&P 500 additions/deletions. Their research indicates that there is no permanent non-fundamental comovement effect after controlling for the characteristics of firms joining the S&P 500. Additions to the index have a systematic increase in earnings per share and market value, and as Chen et al. (2016) showed, positive momentum prior to joining the index. Kasch and Sarkar (2012) therefore suggest that the increased betas of the included are due to these effects, and that the increased comovement is therefore not in excess of fundamentals. Put differently, these studies argue that stock inclusion is not necessarily an information-free event. This is a core assumption when proving excess comovement, and we have therefore in our analyses tried to carefully evaluate this assumption.

Even though Barberis et al. (2005) have received some criticism, the majority of the comovement literature has found similar results and followed their methodology. Boyer (2011) for example, finds evidence strongly supporting excess comovement from index membership from 1981–2004. Boyer (2011) looks at stocks which are moved between the S&P value and growth indexes. He utilises that every six months, S&P rebalances the value and growth subindexes, and uses this rebalancing as an instrument. By definition, the two subindices must have equal market caps. If one index outperforms the other, some stocks must be moved from the winning index to the losing index, to keep the market caps equal. Boyer (2011) looks particularly at the stocks that were moved from one index to the other, despite the fundamentals of the moved stocks becoming more like the index which they left. This means for instance a stock being rebalanced from value to growth, despite the stock itself having become more of a value stock. It is rebalanced only because the value index outperformed the growth index, and the market capitalisation of the value and growth indexes must be equal. Boyer (2011) finds that this stock would now start to comove less with the value index it left, and more with the growth index it joined, despite fundamentally becoming more similar to the value index stocks. This change in comovement occurs in the opposite direction of what fundamentals would suggest.

R. M. Greenwood and Sosner (2007) also extend the work of Barberis et al. (2005), when studying the Japanese Nikkei 225 index. In April 2000, there was a broad redefinition of the Nikkei 225 index, and 30 stocks on the index were replaced. R. M. Greenwood and Sosner (2007) find evidence that upon addition to the index, the stocks become exposed to the shocks from trading experienced by other Nikkei stocks, since they are now purchased and sold in a basket with other index stocks. A robustness test shows that the findings are not driven by characteristics of the included and removed stocks, such as industry or size. The researchers conclude that future risk models should incorporate index membership as an extra characteristic for forecasting of risk, and through this reduce the total variance.

In the UK, Coakley et al. (2004) and Mase (2008) examine the comovement effect of index member changes at the FTSE 100 index in 1992–2002 and 1990–2005, respectively. Similar to the findings of Barberis et al. (2005), both authors find excess comovement from index membership on the FTSE 100 index. However, von Drathen (2014) finds the opposite in his study of the FTSE 100 index when he matches the included stocks with the closest ranked market cap stocks at FTSE 250 which are not included on the FTSE 100 index. Since FTSE includes stocks based on market cap, von Drathen (2014) claims to have controlled for the selection bias that was present in the index by matching with similar stocks.

The majority of studies of comovement are done in the US, Japan and the UK. A common feature of these studies is that the evidence is found on large indexes which base inclusion on market capitalisation. One could question if findings of excess comovement only appear on such indexes due to specific traits. Claessens and Yafeh (2012) on the other hand test comovement for additions to several indexes around the world. The data consists of 40 developed and emerging markets, from 2001 through 2010. They find that for the majority (32/40) of countries, beta and R^2 increase for additions to indices. These comovement effects are greater if the pre-inclusion beta is relatively low, which is a new finding in the literature. Even though the paper finds some variation in the result, the overall conclusion is in support of non-fundamental comovement. A drawback of the study is that for some of the countries, the time frame is limited, and the number of inclusions very low. It is therefore very hard to say much about specific countries based on the research of Claessens and Yafeh (2012).

Norway is one of the countries examined by Claessens and Yafeh (2012). This is to our knowledge the only paper which has performed comovement tests in the Norwegian equity market. Their sample in Norway is, however, very small. It consists of just 11 stocks between 2001 and 2006. Upon inquiry, the authors could only confirm which Norwegian stocks they had observed, not which indexes the stocks were included in. [1] For the 11 stocks they examine, Claessens and Yafeh (2012) find an average change in beta of -0.01, indicating that there is no comovement in Norway. But, as mentioned, the sample size is so small that one cannot conclude much based on it. In our study, we examine 122 stocks, and selecting 11 random ones from that could provide a variety of extreme results.

Overall, the comovement test first employed by Vijh (1994) provides evidence for excess comovement on multiple different indexes. There has, however, been directed criticism about the accuracy of this test. The core of this criticism has been that stock inclusion truly is not necessarily an information-free event. Several critics have pointed out that since the indexes base inclusion on market capitalisation, all inclusions are winner and momentum stocks. This is a large part of our motivation for studying the OBX index – which does not base inclusion on market capitalisation, and consequently, inclusions are not necessarily momentum stocks. The weaknesses in employing the comovement test on the market capitalisation indexes may therefore not apply to the OBX. If then there is no excess comovement on the OBX, the claims that comovement is only found due to the index structure of previous studies are strengthened. If, on the other hand, there is excess comovement on the OBX, then it is likely that index structure is not the cause. We thereby contribute to the literature by shedding light on both the validity of previous comovement results, and their criticism, by being, to our knowledge, the first to study comovement on an index which bases inclusion on volume traded.

3 Data and OBX statistics

In this section, we first present an elaboration of our data and then some summary statistics of the OBX, which highlight some facts that are relevant for this thesis.

[1] We know that they did not study the OBX index, as the stocks they studied never joined the OBX.

The majority of our data is from Oslo Børs Information (OBI). This data set contains data on the prices, returns, volume traded and shares outstanding of all stocks on Oslo Børs from 1980 through 2018. It also contains data on the values of the OBX index, and the Oslo Børs All-Share index (OSEAX), and their price weighted versions. The standard OBX and OSEAX indexes are total return indexes, meaning that they assume dividends are reinvested dividends. That is not ideal for comovement testing, so we run the tests against the version of the OBX that does not include reinvested dividends.

We received data from Bernt Ødegaard about which stocks were included in and removed from the OBX index at each rebalancing. He also provided us with several indexes, such as the Carhart four-factor portfolios and industry portfolios, which he created for his paper on which factors affect the Oslo Stock Exchange (Ødegaard, 2017). Our final set of data is on ownership of the stock indexes. This was collected from the Thomson Reuters Eikon database.

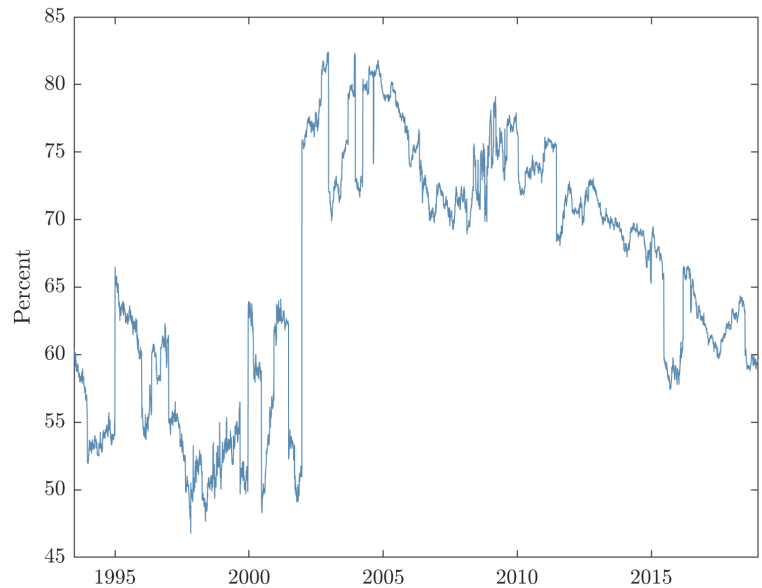
The OBX index normally consists of 25 stocks, and is rebalanced semi-annually (Oslo Børs, 2018). The constituents are generally the 25 stocks with the highest kroner value of volume traded, but Oslo Børs keeps it at their discretion to include stocks by other criteria. One such criteria is a desire to have the OBX index represent the full OSEAX index (Oslo Børs, 2018).

The rules for which stocks are included in the OBX have been unchanged since 1995, and so our analyses go from 1995 through 2018. Over this period, 162 stocks have been added to the OBX index. 40 of these have had to be excluded from our tests due to either mergers and acquisitions, delisting or lack of data, which leaves our total sample at 122 inclusions over 48 rebalances.

Oslo Børs is generally very dominated by a few large firms, and these have tended to be on the OBX index. This means that even though the OBX consists of only 25 stocks out of a total 150-300 stocks at Oslo Børs, the OBX has tended to represent more than half the market value of Oslo Børs. Figure 1 shows how large the OBX market value has been as a percentage of the market value of all shares on Oslo Børs.

One key trait that makes the OBX interesting, is that it is a tradable index, meaning that it is possible to trade the whole index at once through derivatives. This was part

Figure 1: Market value of OBX in percent of the market value of all stocks on Oslo Børs



Note. This graph shows the market value of the OBX index as a percentage of the market value of all stocks on Oslo Børs. The large jump in 2002 stems from Statoil joining the OBX index.

of the motivation for creating the index, and it has been possible to trade options on the OBX since 1990, and futures since 1992 (Oslo Børs, 1997). Oslo Børs notes that in 2017, OBX futures were the most liquid product at Oslo Børs (Oslo Børs, 2017). Based on data available at Oslo Børs' websites, we confirm this to be true. We find that in 2018, 2 723 448 OBX future contracts were made, each consisting of 100 futures on the OBX index. The average value of the OBX index was at 795 in 2018, which puts the market value of the derivatives trades at approximately 216 billion kroner. This is approximately 20% more than the second-most traded product at Oslo Børs in 2018, which was Equinor shares, with trades worth 181 billion kroner. The OBX future trade of 216 billion kroner is equal to approximately 16% of the total trade of shares in Norway.

It is important to note, however, that futures trading on indexes does not entail any actual trading of stocks. At the expiration date, there is merely a cash settlement. Nonetheless, futures trading of indexes may affect the underlying stocks, and has been considered to be a potential source of excess comovement by several comovement authors (Vijh, 1994; R. M. Greenwood & Sosner, 2007).

A second key trait of the OBX index is its ownership structure. The OBX index has a higher share of both foreign ownership and domestic government ownership, than domestic private ownership. At the end of 2018, the Norwegian government owned 50.12% of the OBX index, non-Norwegian investors owned 29.21%, and non-governmental Norwegians owned 20.68%. The government does not change its ownership levels (except in extraordinary circumstances), and the main interest is therefore in ownership levels of the free-floating, non-governmental shares. Of those shares, foreign investors own 58.28%, while private domestic investors own the remaining 41.72%.[2] Foreign investors own substantially more of the OBX than private Norwegians do. This relation is not as clear for the stocks on Oslo Børs that are *not* on the OBX index. Of the free-floating non-OBX stocks, foreign ownership is 48.77% while private is 51.23%. Foreign index funds are particularly clearly owning OBX stocks rather than non-OBX stocks. Non-Norwegian index funds own approximately 11.7% of the OBX index, but only 3.21% of the non-OBX stocks. This highlights the fact that different groups of investors own the OBX and non-OBX stocks.

4 Single factor model

Analysing index inclusion provides an opportunity to study non-fundamental comovement through a natural experiment (R. M. Greenwood & Sosner, 2007). Index inclusion being a natural experiment means that a company's fundamentals should not be expected to change as a result of being included in the OBX index. Stock inclusion into an index can therefore be considered an information-free event, meaning that it signals no change in underlying fundamentals. Most scholars have generally supported this view (Chen, Noronha, & Singal, 2006; Elliott, Van Ness, Walker, & Warr, 2006), but it has recently come under increased criticism by von Drathen (2014), Kasch and Sarkar (2012) and Chen et al. (2016). The critics claim that index inclusions are *not* independent of fundamentals on the S&P 500 index and FTSE 100 index. They therefore state that the studies which found excess comovement, did not correctly control for changes in fundamentals/stock return factors, and that this is what caused them to

[2] Authors' calculations based on Thomas Reuters Eikon ownership data.

find comovement. They claim that the excess comovement found was only apparent, and could be explained by changes in fundamentals.

In this section, we first outline the standard comovement test, which we use as our baseline analysis. We then proceed to create a model which clearly states precisely which assumptions the test has, in order to evaluate whether those assumptions hold for OBX inclusions.

4.1 Empirical methodology

The most established test for comovement is a single-factor regression. This comovement test is employed by Barberis et al. (2005), Vijh (1994), Mase (2008) and Boyer (2011). In order to detect excess comovement we run the following OLS regression separately before and after the stock is added to the OBX index:

$$R_{it} = \alpha_i + \beta_i R_{OBX,t} + e_{it} \tag{1}$$

where R_{it} is the return of stock i at time t, and $R_{OBX,t}$ is the return of the OBX index at time t. After inclusion, we remove the included stock from the OBX index in the regression, so that the stock's new weight in the OBX does not affect the calculated beta.[3] The β_i then shows how much the stock's return moves together with the return of the other stocks on the index.

We run the regression on daily returns, with the pre-inclusion period as the 180 days before the stock was added to the index, and the post-inclusion period as the 180 days after addition. Under the assumption that stock inclusion is an information-free event, the only difference between the beta before inclusion and after inclusion should then be a result of the index inclusion. We define $\Delta\beta$ as the change in beta from before inclusion to after, and calculate the average of these to find the estimate for overall change in comovement: $\overline{\Delta\beta}$.[4] If index inclusion causes increased comovement with the index, the beta should increase as a result of inclusion.

[3]The precise nature of why and how we calculate the OBX without the inclusion, is shown in Appendix A.

[4]Calculating the change in comovement as the average of $\Delta\beta$s has the implicit assumption that the inclusions are independent of each other. We examine this assumption in Section 8.5, and find evidence that it holds

Based on the fundamental view of comovement, however, index membership should not affect stock prices, and the change in beta should therefore be zero. This gives a formal null hypothesis of H_0: $\Delta\beta = 0$.

4.2 Model

The test above relies on several assumptions, most notably that index inclusion is an information-free event. From research in the US and the UK, we know that this assumption may be broken on the S&P 500 and the FTSE 100 indexes (Chen et al., 2016; von Drathen, 2014). We therefore create a model to clearly state all necessary assumptions in order to interpret the $\Delta\beta$ causally. We also build the model to be able to define what the economic magnitude of any excess comovement is, and under which assumptions they hold.

We imagine a simple model where stocks are affected by fundamental factors, and by belonging to a group such as an index. The return of a stock is then defined by:

$$R_{it} = \alpha_i + \sum_{j=1}^{n} \lambda_{ij} f_{jt} + \gamma_i^{Group} * S_{Group} + e_{it} \tag{2}$$

where R_{it} is the return of stock i on day t, f_j are common fundamental factors. These fundamental factors are independent of group belongings. λ_{ij} is stock i's exposure to common fundamental factor j, and n is the total number of fundamental factors. S_{Group} consists of idiosyncratic, non-fundamental group-specific shocks that affect members of the group, but no other stocks. $\gamma_{i,Group}$ represents how sensitive each group member i is to idiosyncratic non-fundamental shocks to the group, and e_{it} is the stock's idiosyncratic risk.

Our focus in this thesis is on stocks added to the OBX index. Prior to inclusion, these stocks were not on the OBX index, but only the Oslo Børs All-Share Index (OSEAX). We divide the OSEAX into two subgroups: OBX stocks and non-OBX stocks. We define non-OBX stocks as all stocks on the OSEAX that are not on the OBX index. The returns of stocks in each of these groups are then as follows:

$$R_{it} = \alpha_i + \sum_{j=1}^{n} \lambda_{ij} f_{jt} + \gamma_i^{OBX} * S_{OBX} + e_{it} \tag{3}$$

$$R_{it} = \alpha_i + \sum_{j=1}^{n} \lambda_{ij} f_{jt} + \gamma_i^{NON} * S_{NON} + e_{it} \tag{4}$$

Our model then assumes that all stocks on the OSEAX are subject to the same set of fundamental factors f_{jt}, but to differing degrees, given by their λ_{ij} loadings. The OBX-stocks differ from non-OBX stocks in that the OBX stocks are subject to idiosyncratic OBX-specific shocks S_{OBX}, while the non-OBX stocks are subject to another set of idiosyncratic shocks S_{NON}. These two shocks are therefore by definition assumed to be uncorrelated.

The returns of the indexes are value-weighted averages of the returns of their constituents. They can therefore be formulated as:

$$R_{OBX,t} = \alpha_{OBX} + \sum_{k=1}^{n} \lambda_{OBX,k} f_{kt} + 1 * S_{OBX} + e_{OBXt} \tag{5}$$

$$R_{NON,t} = \alpha_{NON} + \sum_{l=1}^{n} \lambda_{NON,l} f_{lt} + 1 * S_{NON} + e_{NONt} \tag{6}$$

where α_{OBX} is the value-weighted average of α_i, $\lambda_{OBX,k}$ is the value-weighted exposure of each λ_{ij}, and signals OBX index' exposure to fundamental factors. Since shocks S_{OBX} directly affect the return of the OBX index in a 1:1 fashion, the sum of the value weighted γ_i equals 1.

This section so far has defined the returns of the different stocks and indexes. The purpose of that is to find what results running the single-factor model will yield. The single-factor regression is:

$$R_{i,t} = \alpha_i + \beta_i * R_{OBX} + e_{it} \tag{1}$$

We run the regression both prior to and after inclusion, and then calculate the $\Delta\beta$ as $\beta^a - \beta^b$. Prior to inclusion, the stock is a non-OBX stock, and has the return of a non-OBX stock. After inclusion, it has the return of an OBX stock.

When the single factor regression is run on a non-OBX stock, the expected estimated beta is equal to:

$$\beta_i^b = \frac{cov(R_i^b, R_{OBX}^b)}{var(R_{OBX}^b)} \tag{7}$$

In this model, that is equal to:

$$\beta_i^b = \frac{cov(\alpha_i + \sum_{j=1}^{n} \lambda_i^b * f_j t + \gamma_i^{b,NON} S_{NON} + e_{it}, \alpha_{OBX} + \sum_{j=1}^{n} \lambda_{OBX,j} f_{jt} + S_{OBX} + e_{OBXt})}{var(\alpha_{OBX} + \sum_{j=1}^{n} \lambda_{OBX,j} f_{jt} + S_{OBX} + e_{OBXt})} \tag{8}$$

As non-fundamental group shocks and firm specifics risk are idiosyncratic, we assume that they are uncorrelated with the other factors in the model. This gives:

$$\beta_i^b = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} \lambda_{ij}^b \lambda_{OBXk}^b cov(f_j, f_k)^b}{\sigma_{OBX}^{2,b}} \tag{9}$$

That is the beta a stock has prior to inclusion. Following inclusion, the stock will be exposed to the OBX shocks. That is:

$$\beta_i^a = \frac{cov(\alpha_i + \sum_{j=1}^{n} \lambda_i j^a * f_j t + \gamma_i^{a,OBX} S_{OBX} + e_{it}, \alpha_{OBX} + \sum_{j=1}^{n} \lambda_{OBX,k}^a f_{jt} + S_{OBX} + e_{OBXt})}{var(\alpha_{OBX} + \sum_{j=1}^{n} \lambda_{OBX,j} f_{jt} + S_{OBX} + e_{OBXt})} \tag{10}$$

Just as in the before case, but the shock term remains, since both the stock and the OBX index are subject to the S_{OBX} shocks. The β_i^a term therefore becomes

$$\beta_i^a = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} \lambda_{ij}^a \lambda_{OBXk}^a cov(f_j, f_k)^a + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2}{\sigma_{OBX}^{2,a}} \tag{11}$$

When we calculate $\Delta\beta_i = \beta_i^a - \beta_i^b$, our estimate is in other words equal to:

$$\Delta\beta_i = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} \lambda_{ij}^a \lambda_{OBXk}^a cov(f_j, f_k)^a + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2}{\sigma_{OBX}^{2,a}} - \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} \lambda_{ij}^b \lambda_{OBXk}^b cov(f_j, f_k)^b}{\sigma_{OBX}^{2,b}} \tag{12}$$

This equation can be simplified by the assumption that the variance of the OBX index is equal in expectancy over time. That is, $\sigma_{OBX}^{2,a} = \sigma_{OBX}^{2,b}$. We examine this assumption and its consequences in Appendix B.

To make the equation easier to read, we define C as the variance-covariance matrix $\sum_{j=1}^{n} \sum_{k=1}^{n} cov(f_j, f_k)^a$, where C_{jk} is the covariance between fundamental j and fundamental k. The change in beta for a stock included in an index can then be written as:

$$\Delta\beta_i = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} [\lambda_{ij}^a \lambda_{OBXk}^a C_{jk}^a - \lambda_{ij}^b \lambda_{OBXk}^b C_{jk}^b] + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2}{\sigma_{OBX}^2} \tag{13}$$

Three final assumptions must hold in order for $\Delta\beta$ to be a good, unbiased estimator of excess comovement.

Assumption 1: Inclusion is an information-free event

Inclusion into the OBX index is an information-free event for the stock joining the index. This means that joining the OBX index neither signals nor causes changes in the stock's fundamentals. That is, the stock's loadings on fundamental factors are unchanged: $\lambda_{ij}^{a} = \lambda_{ij}^{b}$

Assumption 2: OBX loadings do not systematically change

The OBX index' loadings on fundamental factors are unchanged from prior to inclusion until after, that is: $\lambda_{OBXk}^{a} = \lambda_{OBXk}^{b}$

Assumption 3: The fundamental factors do not systematically change

The variance-covariance matrix C does not change between periods, so that $C_{jk}^{a} = C_{jk}^{b}$. Recall that the variance-covariance matrix signals the variance of shocks to fundamental return factors, and the covariance between shocks to different fundamental return factors. This assumption is in other words amounts to assuming that the shocks to the fundamental return factors are a stochastic variable which draws from the same distribution over time.

These three assumptions will not hold for every stock, but it is feasible to assume that they hold in expectancy. These assumptions will be challenged in later sections, but provided that they hold in expectancy, the expected $\Delta\beta_i$ is:

$$\Delta\beta_i = \frac{\gamma_i^{OBX} * \sigma_{S_{OBX}}^2}{\sigma_{OBX}^2} \tag{14}$$

$$\overline{\Delta\beta} = \frac{1}{n}\sum_{i=1}^{n} \frac{\gamma_i^{OBX} * \sigma_{S_{OBX}}^2}{\sigma_{OBX}^2} \tag{15}$$

The expected change in beta coefficient is equal to the stock's loading toward the non-fundamental, OBX-specific shocks, multiplied by the variance of those shocks, divided by the variance of the OBX index. Since shocks S_{OBX} affect the OBX index 1:1, the value-weighted average of γ_i^{OBX} is equal to 1. This means that the $\Delta\beta_i$ shows approximately how large a share of the variation in the OBX index can be explained by non-fundamental, group-specific shocks. A $\overline{\Delta\beta}$ of 0.06 would for instance signal that six percent of the variation in OBX returns are due to comovement in excess of fundamentals. A $\overline{\Delta\beta}$ of approximately 0 would on the other hand support the fundamental view of comovement.

4.3 Results

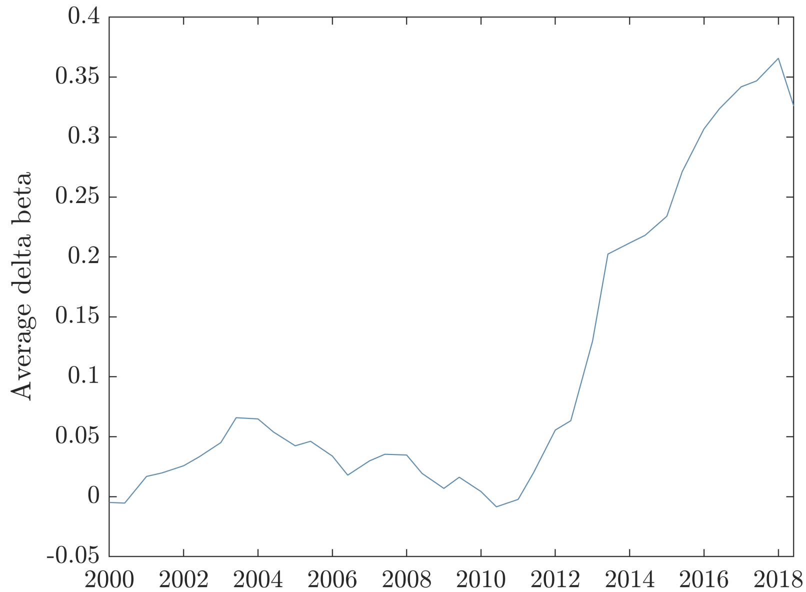
Table 1 reports the results of the single-factor regression. For the full period of 1995-2018, the average change in the slope coefficient is 0.0720, significant at the 1% level. This result is primarily driven by the later years, however, as there were little signs of excess comovement before 2010. Figure 2 illustrates this with the rolling 5-year average $\Delta\beta$ over time. From 1995 to 2010, the $\Delta\beta$ tends to be low and insignificant, but after 2010, it started to dramatically increase.

This strong time-trend means that it is worthwhile to analyse the different sub-periods of our sample. We divide our sample into three sub-periods, with cutoff points in January 2003 and January 2009. January 2009 is chosen as this is just after the financial crisis, and it may be that something changed due to the financial crisis which spurred a growth in OBX-specific shocks. The selection of January 2003 is more arbitrary, and comes of a desire to have approximately equally many stocks in each sample.

In the first two sub-periods of 1995-2002 and 2003-2008, there are no signs of comovement, as $\Delta\beta$ is low and insignificant. In the final, however, the $\Delta\beta$ is estimated to be 0.2191. If the model's assumptions are true, that means 21.91% of the variation of the OBX index in this period stems from OBX specific shocks. If true, that has profound implications for diversification and risk management.

The standard errors presented in the table deserve some comment. These standard errors assume independence between inclusions. We evaluate that assumption in Section 8.5, where we examine the standard errors more closely. We find that the assumption that standard errors are independent holds in Norway, and therefore use them for the majority of the paper.

Figure 2: Five-year average change in slope coefficient of single-factor regression



Note. This graph shows the average change in beta from before inclusion to after inclusion, over the five years prior to the data point. As an example, the data point in 2008 is the average delta beta between January 2004 and January 2008.

Table 1: Effects of inclusion into OBX

	$\overline{\Delta\beta}$	SE($\overline{\Delta\beta}$)	tStat	ΔR^2	nObs
1995–2018	0.0720	0.0244	2.9497	0.0334	122
1995–2002	-0.0011	0.0364	-0.0297	0.0140	54
2003–2008	0.0258	0.0460	0.5611	0.0379	34
2009–2018	0.2191	0.0501	4.3714	0.0597	34

Note. This table reports the summary statistic of the effect of inclusion for the different time periods, calculated by regressing the stocks return on the OBX-return prior to and after inclusion. $\overline{\Delta\beta}$ is the average change in beta, SE are the heteroskedasticity robust standard errors. tStat is the variable test statistic. nObs is the number of observations and $\Delta\ R^2$ is the change in variation explained by OBX-return.

To provide some context for these estimates, we compare the $\overline{\Delta\beta}$ to the ones previous researchers have found in other countries. Table 2 shows a comparison to the seminal studies in the US, UK and Japan. In the US, the magnitude from 1988–2008 is similar to the one we find in Norway from 2009 through 2018. The magnitudes in the UK for 1998–2005, as well as Japan in 2000, are far higher than the one observed on the OBX. These countries also show a growing trend, with the later periods displaying much higher $\overline{\Delta\beta}$ than the earlier ones.

Table 2: Results obtained from major studies

	Barberis (2005)	Barberis (2005)	Mase (2008)	Mase (2008)	Greenwood (2013)
Market	US	US	UK	UK	JP
Index	S&P 500	S&P 500	FTSE 100	FTSE 100	Nikkei 225
Period	1976–1987	1988–2008	1990–1998	1998–2005	2000
$\overline{\Delta\beta}$	0.067	0.214	0.147	0.451	0.45

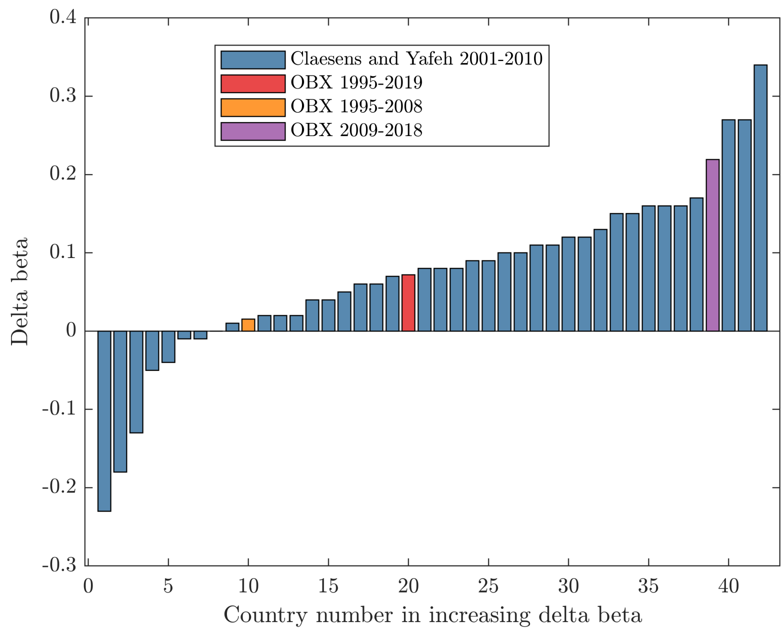
Note. This table presents the average change in beta from major studies on the S&P 500, FTSE 100 and Nikkei 225. The study by Greenwood (2013) on the Nikkei 225 was a single event study in April 2000.

There are relatively few comovement studies performed on indexes in countries other than the US, UK and Japan. The main exception is Claessens and Yafeh (2012) who study comovement in 40 countries, during the period between 2001 and 2010. In Figure 3, we compare the results of our test to theirs. Only three countries in their sample saw a higher estimate for $\overline{\Delta\beta}$ between 2001 and 2010 than our estimate for the OBX for 2009–2018. As nobody has performed a study in those countries for the data after Claessens and Yafeh (2012), we cannot compare with tests for the same time period. We do not know if those countries have displayed a growth in comovement similar to the one we have seen in Norway.

One of the countries studied in the paper by Claessens and Yafeh (2012) was Norway. This is, to our knowledge, the only comovement test that has been done in Norway prior to ours, but consists of analysing just 11 stocks from 2001 to 2006. These 11 stocks showed no sign of comovement, with an average $\Delta\beta$ of -0.01. This is a similar result to what we find for the 2003–2008 period, but in truth, studying 11 stocks is too little to be able to say anything meaningful about comovement.

In conclusion, we find that excess comovement has risen sharply in Norway, and that the economic magnitude for the period 2009–2018 is high. If the model's assumptions hold, 21.91% of the variance on the OBX is caused by group-specific shocks to the OBX index. Compared to previous studies, this is high, but lower than for instance the UK and Japan.

Figure 3: Results compared to those of Claessens and Yafeh (2012)



Note. This graph shows the average change in beta for each country studied by Claessens & Yafeh (2012) compared to our results at the OBX index prior and post the financial crisis. The delta betas are estimated by employing the standard comovement test.

5 Testing the assumptions of the single factor model

Investigating excess comovement through index inclusion with a single factor model is the most established method in the comovement literature. However, as we showed in Section 4.2 the methodology relies on several critical assumptions that need to hold in order to obtain an unbiased result. In this section we therefore test our results from Section 4.3, and whether the assumptions hold. We first extend the model to a multi-factor setting, examining whether adding more priced risk factors to model produces results that differ from the single-factor model. In the subsequent subsection, we evaluate whether momentum affects comovement in Norway, as it has in other countries. Afterwards, we examine whether industry trends can explain anything about comovement, before we analyse whether nonsynchronous trading amplifies our results. Lastly, we perform several tests to evaluate whether liquidity and volume traded is a driver of comovement.

5.1 Proxies for changes in fundamentals

Consistent with findings of Vijh (1994), Barberis et al. (2005) and Mase (2008), we find in Section 4.3 significant excess comovement when a stock is added to OBX. However, none of these analyses control for potential changes in loadings on common factors for the specific firm, around index inclusion (Kasch & Sarkar, 2012). Barberis et al. (2005) do however compare their findings with matching firms from the same industry and with similar growth size and changes. Nevertheless, they do not observe changes in common factors for the included firms as suggested by Kasch and Sarkar (2012).

Unlike arbitrage pricing theory (APT) that does not limit the number of risk factors (Ross, 1976), practical use of the capital asset pricing model (CAPM) relies on systematic market risk as the only exposure (Lintner, 1965; Sharpe, 1964). Since fundamental comovement is defined by APT, a single factor model such as the CAPM which is commonly used by previous studies, will not necessarily detect changes in loadings on systematic factors upon stock inclusions.

As described in Section 4.2, we need to assume that loadings on fundamental factors are constant, e.g. $\lambda^a_{ij} = \lambda^b_{ij}$, in order to obtain a clean estimate of potential excess comovement.

We can, however, not directly observe the loadings of the stocks against all fundamentals, as most fundamentals are inherently hard to measure. But we can use certain proxies for fundamentals, and evaluate whether or not they are changing. There is extensive empirical evidence that firm-size, book-value and momentum can explain a significant share of cross-sectional variation in the CAPM beta (Carhart, 1997; Fama & French, 1993). Some argue that these factors are pricing anomalies, while others argue that they are proxies for fundamental risks. We consider them as the latter, and run the following regression on daily returns, with pre-event regression of 180 days before index addition and a post-event regression of 180 days after the inclusion of the stock.

$$R_{it} = \alpha_i + \beta_{i1} R_{OBX,t} + \beta_{i2} SMB_t + \beta_{i3} HML_t + \beta_{i4} PR1YR_t + e_{it} \tag{16}$$

Where SMB (small minus big) is the premium of the size factor, HML (high minus low) is the premium of the book-to-market factor, and $PR1YR$ (prior one year return) is the premium of the momentum factor.[5] Factor portfolios for SMB, HML are calculated as by Fama and French (1998), and $PR1YR$ as by Carhart (1997), using Norwegian data by Ødegaard (2017).

Our null hypothesis is that inclusion is an information-free event, which means that the proxies for fundamentals are unchanged, that is: $H_0: \Delta\beta_2 = 0, \Delta\beta_3 = 0, \beta_4 = 0$. The alternative hypothesis is that inclusion is not an information-free event, and that the loadings on the proxies for fundamentals change after inclusion: $H_1: \Delta\beta_2 \neq 0, \Delta\beta_3 \neq 0, \beta_4 \neq 0$. The results are presented in Table 3.

Table 3: Multifactor regression with OBX as variable

	$\overline{\Delta\beta_{OBX}}$	$\overline{\Delta\beta_{SMB}}$	$\overline{\Delta\beta_{HML}}$	$\overline{\Delta\beta_{PR1YR}}$
1995–2018	0.09717**	0.01824	-0.01236	0.014653
1995–2002	-0.0250	-0.1040*	0.0876**	0.0128
2003–2008	0.0556	0.0931	-0.2112***	0.0494
2009–2018	0.3054***	0.0983	0.0548	-0.0181

Note: This table shows the average change for $\Delta\beta_{OBX}$, $\Delta\beta_{SMB}$, $\Delta\beta_{HML}$ and $\Delta\beta_{PR1YR}$, calculated by a multifactor model for the included stocks prior to and after inclusion. β_{OBX} is the loading on OBX, β_{SMB} is loading on small-cap companies, β_{HML} is loading on high book value to market value ratio companies and β_{PR1YR} is the loading on the PR1YR momentum factor. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

None of the control variables have significant changes in their loadings for the full period. The change in HML has a significant loading in two of the sub-periods, but with changes in opposite directions. ΔSMB also has different signs in the different periods. There is in other words no clear trend in how the loadings for how either of the three control factors change.

Our primary interest is in whether adding SMB, HML and $PR1YR$ affects the change in comovement. The $\Delta\beta_{OBX}$ is actually substantially higher in this regression than in the single-factor. For the full period, it is 0.09717, compared to 0.07203 in the single-factor, an increase of 0.02514. In the final period, $\Delta\beta_{OBX}$ is 0.3054 here, up from 0.2191 in the single-factor. It is therefore clear that the reason for the increased comovement is not that the inclusions see increased loadings on these risk factors.

[5] By using the UMD factor of Fama and French (1998) we obtain similar results as when we use the $PR1YR$ factor from Carhart (1997).

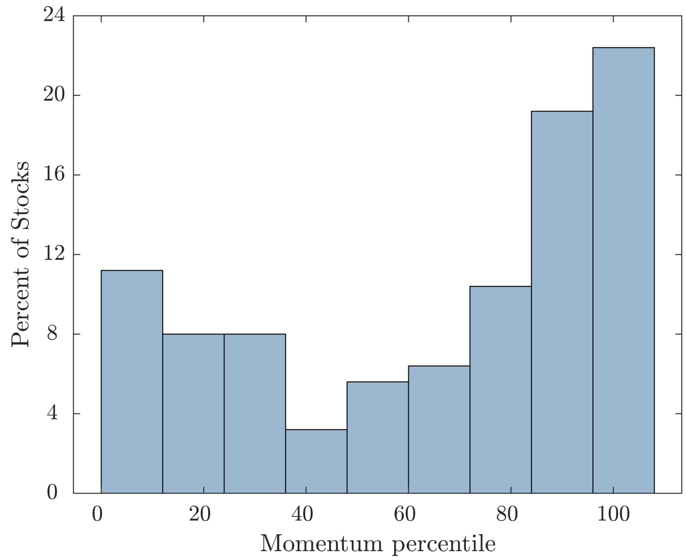
It is important to note, however, that the results in this subsection do not necessarily signal a higher economic magnitude of the comovement effect than the single-factor model did. The $\Delta\beta_{OBX}$ here shows how much the loading on $\Delta\beta$ increases after controlling for SMB, HML and $PR1YR$. That is a different meaning from the one in the single-factor model, which we could interpret as showing how large a share of the variation in OBX was explained by non-fundamental OBX-specific shocks.

5.2 Momentum

Recent critics as Kasch and Sarkar (2012) and Chen et al. (2016) have made claims that the vast majority of the excess comovement found by Vijh (1994) and Barberis et al. (2005) on the S&P 500 index, was in fact a result of momentum. Chen et al. (2016) showed that the majority of the stocks included in the S&P had experienced a high return over the year before inclusion. This is due to the S&P 500 basing membership on market capitalisation. It's impossible to go from being outside the top 500 largest firms to being one of the top 500 largest firms, unless the value of the firm has increased. Chen et al. (2016) claim that the increase in beta after index inclusion comes as a result of the momentum prior to inclusion. They perform a matched sample test, where they see what happens with stocks that had a similar momentum growth, but didn't join the S&P 500 index, and find that these stocks also saw a large increase in comovement. The authors conclude that it was momentum that caused the increased comovement, and not index inclusion.

We examine the extent to which stocks that join the OBX index are momentum stocks. On average, additions to the OBX index have outperformed 63% of stocks on the OSEAX over the six months prior to the stock's inclusion on the OBX index. This means that the average addition is a momentum stock. Since inclusion is not linked to market capitalisation, however, not all additions are momentum stocks. This fact is shown in Figure 4.

Figure 4: Distribution of additions by their momentum percentile prior to joining



Note. This histogram shows to which extent OBX additions are momentum stocks. The x-axis shows how many percent of stocks the addition outperformed over the six months prior to inclusion. The Y-axis shows how many percent of additions belong in each bucket. Had inclusion been independent of momentum, this distribution should have been uniform, and the graph flat.

While there is a tendency towards additions being momentum stocks, many additions were among the worst performers on the OSEAX over the six months prior to inclusion. This variation in our data allows us to perform tests that cannot be performed on the market capitalisation based indexes – they do not observe the counterfactual "loser additions" that performed poorly prior to inclusion. They therefore have to resort to a matched sample test. But on the OBX index, we observe both winner and loser additions, and therefore perform tests to directly examine the extent to which momentum affects comovement.

We do this through running a second-stage regression where we explain the $\Delta\beta$ found from the univariate regression as a result of which momentum percentile the stock was in, prior to inclusion:

$$\Delta\beta_i = \eta_0 + \eta_1 * MomentumPercentile_i + e_i \tag{17}$$

Our null hypothesis is that inclusion is an information-free event, i.e. that $\Delta\beta_i$ is not affected by the momentum prior to inclusion. This gives $H_0 : \eta_1 = 0$. The alternative hypothesis is that the findings of Kasch and Sarkar (2012) and Chen et al. (2016) apply in Norway too. Winners become more like other winners, and therefore the stocks that were previously winners, should now become more like the stocks on the OBX index. The results of the regression are shown in Table 4.

Table 4: Momentum second stage regression

	Estimate	SE	tStat
η_0	0.087857	0.072424	1.2131
η_1	0.014416	0.0993	0.14517
Regression R^2	0.000185		
Adjusted R^2	-0.00859		

Note. This table reports the summary statistic of the second stage regression, calculated as the average change in beta regressed on momentum percentile. η_1 is the loading on the momentum percentile, SE is the heteroskedasticity robust standard error, and tStat is the variable test statistic.

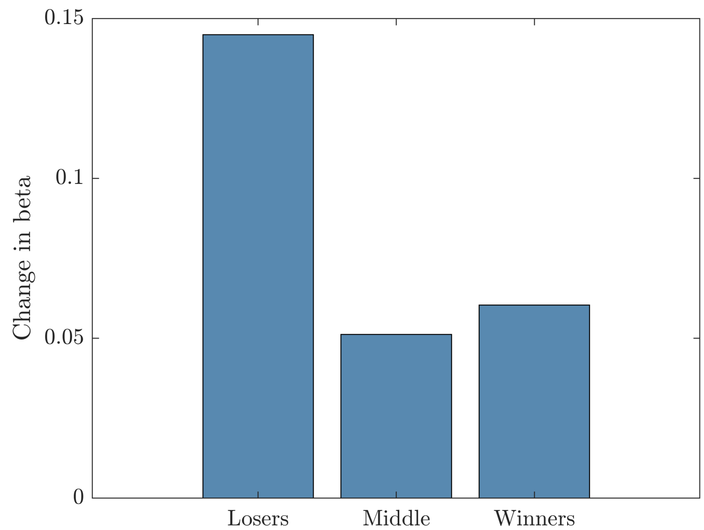
The most striking finding in Table 4 is the negative adjusted R-squared. This means that the momentum prior to inclusion has no predictive power on the increase in co-movement after. The η_1 result is also low, and far from significant. These results are a clear indication that momentum is not what affects comovement.

To sanity check and illustrate these results, we perform a second test, illustrated in Figure 5. We divide the additions into three groups based on prior momentum: Losers, middle, and winners. The losers category consists of stocks that are in the bottom third performers in the six months before joining (the first three bars in Figure 4). The middle consists of stocks that are the middle third, and the winners are in the top third performers. We then calculate the average change in beta for each of these groups, by running the univariate regression on each subgroup. That results are shown in Figure 5.

These results show the opposite trend of our hypothesis. We have no theoretical reason to assume that the low-momentum loser stocks should see a larger increase in comovement than the others, and the groups are not statistically significantly different from each other. Nonetheless, it is a very clear indication that momentum is not a driver of comovement on the OBX index.

The question then is, why do we find different results from Chen et al. (2016). There are two possible reasons for this. Either, momentum matters less for comovement than Chen et al. suggest, or momentum simply matters less in Norway. Research by Næs, Skjeltorp, and Ødegaard (2009) suggest that the latter may be the reason. They replicate

Figure 5: Change in beta for stocks in momentum buckets



Note. The histogram shows the average $\Delta\beta$ of three categories. Losers, which were in the bottom third performers on OSEAX over the six months prior to inclusion on the OBX index. Middle, which were in the middle third, and winners, which were in the top third performers.

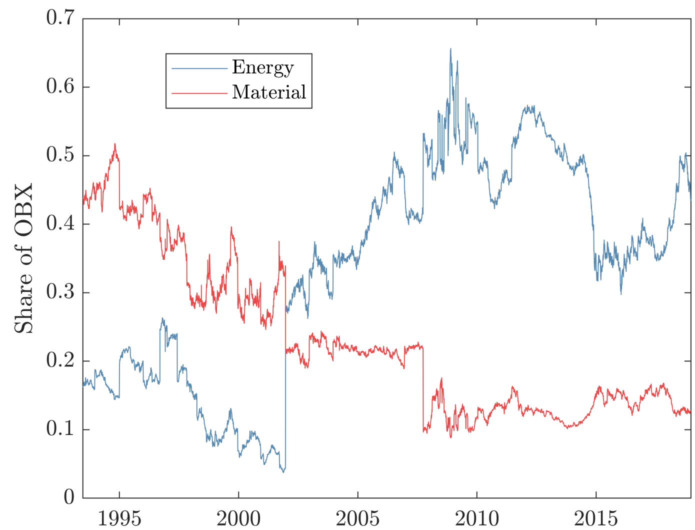
a study by Jegadeesh and Titman (1993), which consists of buying the top decile best performing stocks, and selling the bottom decile worst performing stock. This has been shown to create excess returns in the US (Jegadeesh & Titman, 1993), and in 35 other countries (Rouwenhorst, 1998). However, the strategy does not provide excess returns when employed in Norway (Næs et al., 2009). From 1990–1999, it does in fact provide statistically significant negative results.

In conclusion, there are no signs that the increased comovement from inclusion on the OBX index can be explained by momentum. This may be a sign that the existing comovement literature overestimates the significance of momentum, but we consider it more likely that this is simply a quirk of the Norwegian stock market. Regardless of which is the case, our findings show that momentum cannot explain the excess comovement found in Norway.

5.3 Industry

The OBX index is dominated by a few large sectors. In the 1990s, the dominant sector was the material sector, and after 2002, the energy sector has generally made up around

Figure 6: Energy and material sectors as a percentage of OBX index over time



Note. This figure shows the energy and material sectors as a percentage of OBX index from 1992-2018. It is calculated by taking the combined market value of all stocks in each of the sectors, and dividing that by the market value of the full OBX index.

40% of the index. The share of these two sectors over time is shown in Figure 6.[6]

As OBX is a value-weighted index, OBX's return will to a large extent be influenced by the return to the largest sectors at a given time. This can potentially affect the results in Section 4.3. If, for example, oil-related stocks are systematically included in the OBX together, or just when there is a price increase in the oil industry, the oil sector will make up a larger part of OBX after inclusion than before. Hence, the OBX index' loadings on fundamental factors may in fact change prior to and after inclusion. This would violate our second assumption, i.e. $\lambda^a_{OBXk} \neq \lambda^b_{OBXk}$. As discussed in Section 4.2, we need this assumption to hold in order to estimate an unbiased estimate for excess comovement.

In order to test if industry-specific factors may violate our second assumption, we run the following test for the 180 days prior to, and 180 days after, inclusion:

$$R_{it} = \Omega_{0i} + \Omega_{1i} R_{OBX} + \Omega_{2i} R_{Industry,t} + e_{it} \tag{18}$$

where $R_{industry}$ is the return of the value-weighted industry portfolio that the stock belongs to (Næs et al., 2009). The industry is defined from the Global Industry Classification Standard (GICS).

[6]The dramatic increase in 2002 is due to Statoil joining the OBX index.

Our null hypothesis is that the fundamental loadings on industry are unchanged from index membership. This also means that the change in loading on the OBX market should be unchanged in this regression from the univariate. Formally expressed as $H_0 : \Delta\Omega_1 = \Delta\beta$.The alternative hypothesis is that the additions have changed loadings after inclusion. This would lead to the $\Delta\beta$ yielding an incorrect result, and being different from the $\Delta\Omega_1$ observed in this test: $H_1 : \Delta\Omega_{1i} \neq \Delta\beta$. The results are shown in Table 5.

Table 5: Results of regression controlling for factor loadings and shocks to industry

	OBX	Industry
$\overline{\Omega^b}$	0.4216	0.5931
$\overline{\Delta\Omega}$	0.0736	0.0360
SE($\overline{\Delta\Omega}$)	0.0394	0.0323

Note. This table shows the estimated coefficients of stock return regressed on OBX and industry, calculated prior to and after inclusion. $\overline{\Omega^b}$ is the average loading on OBX and the associated GICS sector for each stock before inclusion. $\overline{\Delta\Omega}$ is the average change in loading on OBX $(\Delta\Omega_1)$ and the associated GICS sector for each inclusion $(\Delta\Omega_2)$. SE is the heteroskedasticity robust standard error.

These results give support to the null hypothesis. $\Delta\Omega_1$ in this regression is virtually identical to $\Delta\beta$ in the original single-factor regression. $\Delta\Omega_2$ is positive, but not statistically significant.

We also examine whether the OBX index becomes more like the industry of additions after the additions join. That is not the case. Concretely, we run the regression $R_{OBX,t} = \eta_0 + \eta_1 R_{Industry,t} + e_t$ for each industry every time a stock of that industry is included. As usual, we run it for the 180 days before and after inclusion separately. The $\Delta\eta_1$ is estimated to be -0.0082. This means that the comovement is not driven by the OBX index becoming similar to the industries of the additions.

5.4 Non-trading effects

Microstructure research shows that findings of daily returns may suffer spurious upward bias due to non-trading effects (Dimson, 1979; Scholes & Williams, 1977). As OBX represent the most tradable shares in the Norwegian stock market, there is reason to believe that our results in Section 4.3 may be explained by the liquidity construction of OBX. This can be explained by the following example.

Stocks on OBX are by definition trading more often in one day than non-OBX shares. Any potential market wide news at the end of a trading day will more likely be captured on the OBX return. Stocks that are not traded so often (non-obx stocks) are less likely to be traded between the market wide news hits and the end of the trading day. The return for that day will thus be less likely to reflect the new information. The non-trading hypothesis thus predicts that companies that are traded more often (companies included in the OBX) will receive an increase in beta due to the fact that stock-prices observe new information faster relative to OBX return.

To control for nonsynchronous trading effects we adapt Dimson (1979) adjustments when calculating our beta values. This method is suggested by Vijh (1994) and Dimson (1979)) when estimates are potential suffering from non-synchronous trading effects.

We run the following regression with OLS on daily return, with pre-event regression of 180 days before index addition and a post-event regression of 180 days after the inclusion of the stock:

$$R_{it} = \alpha_i + \sum_{k=-n}^{n} \beta_i^k OBX_{j,t+k} + e_{it} \tag{19}$$

To estimate the true regression coefficient we include leads and lags from OBX and sum the coefficient in our regression. Then we estimate the overall beta as the sum of all the leads and lags. By increasing the number of non-synchronous terms, the potential bias will be reduced. However, increasing the number of coefficients comes with a cost as the lagged and leading coefficients suffer from estimation error (Dimson, 1979).

The results are presented in Table 6 and indicate that adding leads and lags to the regression has little effect on the average $\Delta\beta$ of the stocks. The conclusion is therefore that non-synchronous trading does not appear to affect the comovement for stocks included on the OBX.

5.5 Volume traded and liquidity

On market capitalisation based stock exchanges such as the S&P 500 index, stocks that see an increase in market capitalisation, i.e. momentum stocks, see an increased beta

Table 6: Dimson delta betas

	1995–2018	1995–2002	2003–2008	2009–2018
No leads or lags	0.0720	-0.0011	0.0258	0.2191
1 lag	0.0687	0.0037	0.0101	0.2137
2 lags	0.0690	0.0132	0.0144	0.2256
1 lead & 1 lag	0.0713	0.0096	0.0077	0.2248

Note. This table shows the average change in beta with three different numbers of leads and lags, divided into different time-periods.

towards the index (Chen et al., 2016). In other words, an increase in the metric that decides inclusion into the index, increases comovement with the index regardless of inclusion.

We have in this paper shown that momentum does not increase comovement with the OBX index. Momentum is not the metric that decides inclusion into the OBX index, instead the Norwegian krone value of volume traded is. We examine whether increased volume traded causes increased comovement in Norway. Therefore, we run a second-stage regression on the betas:

$$\Delta\beta_i = \zeta_0 + \zeta_1 * log\frac{V_i^a}{V_i^b} + e_i \tag{20}$$

where V_i^b and V_i^a are the cash value of volume traded prior to and following inclusion respectively. If volume traded affects comovement, then ζ_i should be positive, while it should be zero otherwise. We therefore test the null hypothesis: $H_0 : \zeta_1 = 0$. The results are shown in Table 7.

Total volume traded affects the comovement of stocks. The effect is particularly clear in the last period, but also present in the earlier ones. H_0 is clearly rejected for the last period.

The explanatory power of the relation between volume traded and comovement is fairly strong. The median OBX inclusion sees an increase in cash volume traded of 23.87% from the 180 days before to inclusion, to the 180 days after (this median is approximately the same for each period).

The effect can also be shown through the fact that stocks which see a decrease in volume traded, do not see an increase in comovement. Stocks with a decrease in volume

Table 7: Regression of change in volume traded on comovement

	ζ_0	ζ_1	R^2
1995–2018	0.047	0.13311**	0.0431
1995–2002	-0.009145	0.053509	0.0122
2003–2008	0.0083463	0.15868*	0.0878
2009–2018	0.19001**	0.34691**	0.127

Note. This table presents the effect of the loading on change in traded volume on change in beta for each specific stock, divided into different time periods. ζ_0 is the intercept and ζ_1 is the slope coefficient. R^2 signals the variation explained by the model. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

traded following index inclusion see an average $\Delta\beta$ of -0.056 on average, compared to an average of 0.1876 for those that see increased volume traded following inclusion. Volume traded has a strong impact on comovement, and the single-factor model may incorrectly be picking up part of that as excess.

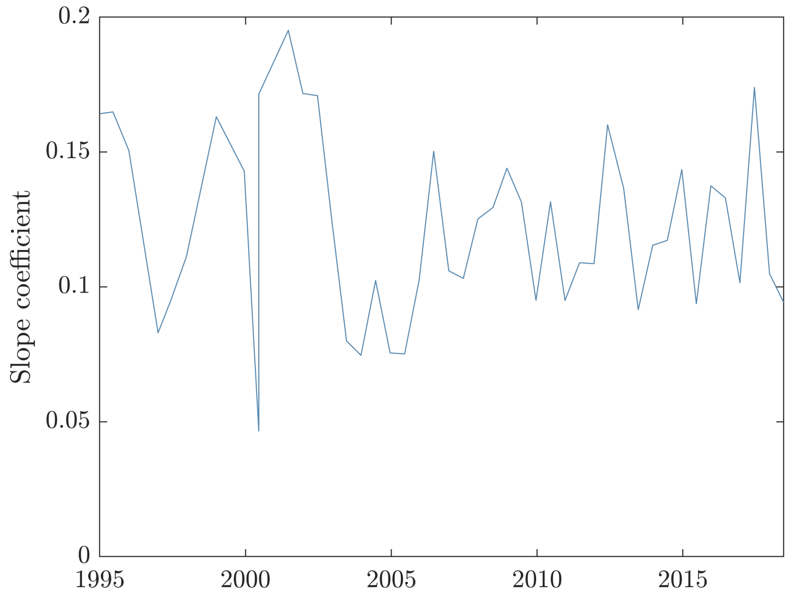
The effect of volume traded on beta is not limited to stock inclusions. We run the regression $\beta_i = \eta_0 + \eta_1 * log(V_i) + e_t$ for the top 100 most liquid non-OBX stocks, for each OBX rebalancing period, and find that η_1 is significant at the 1% level for 47 out of 48 periods (and at the 5% level for the last), with a coefficient around 0.12. This is illustrated in Figure 7.

To the best of our knowledge, no other study has looked at precisely the relation between the cash value of volume traded and comovement, but some studies have looked at a similar measure – the Amihud illiquidity statistic (Amihud, 2002). This measure is useful, as we seek to determine whether the reason we find that volume traded increases comovement, is that increased volume traded works as a proxy for the liquidity of the stock, and that increased liquidity causes the comovement. The Amihud illiquidity measure is defined as

$$ILLIQ_i = \frac{1}{n} \sum_{t=1}^{T} \frac{abs(R_{it})}{V_{it}} \tag{21}$$

where V_{it} is the cash value of volume traded of stock i on day t, $abs(R_{it})$ the absolute value of its return, and T the total number of days the measure is calculated for. Amihud considers this as "the daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact".

Figure 7: Average effect of volume traded against OBX.



Note. This graph shows the extent to which the volume traded of a stock, affects that stock's comovement with the OBX index. The y-axis is the average η_1 of the regression $\beta_i = \eta_0 + \eta_1 * log(V_i) + e_t$ for the 100 most liquid non-OBX stocks.

We calculate the ILLIQ measure for the 180 days prior to inclusion and the 180 following inclusion, and then run the second-stage regression with the change in the ILLIQ measure as the explanatory variable. $\Delta\beta_i = \zeta_0 + \zeta_1 * log\frac{ILLIQ_i^a}{ILLIQ_i^b} + e_i$. If liquidity causes increased comovement with the OBX index, then ζ_1 should be positive. The results are shown in Table 8. Note that since ILLIQ is an illiquidity measure, a decrease in loading signals an increase in liquidity.

The change in the Amihud illiquidity measure explains much less of the comovement than the change in volume traded did. The ζ_1 is not significant even at the 10% level for any sub-period, and the R^2 is low. While we rejected H_0 when volume traded was the explanatory variable, we cannot reject it using ILLIQ as the explanatory variable. This may appear surprising at first, as volume traded and ILLIQ are almost inverse of each other, but recall that we are looking at excess comovement, and what its economic significance is per our model:

$$\overline{\Delta\beta} = \frac{1}{n}\sum_{i=1}^{n}\frac{\gamma_i^{OBX} * \sigma^2_{S_{OBX}}}{\sigma^2_{OBX}} \tag{22}$$

The excess comovement shown in $\Delta\beta$ is an increase in the variance of the stock. If

Table 8: Regression of change in the Amihud ILLIQ measure on comovement

	ζ_0	ζ_1	R^2
1995–2018	0.056094*	-0.056371*	0.0258
1995–2002	0.0081552	-0.058621	0.0436
2003–2008	0.01225	-0.048639	0.0206
2009–2018	0.18901**	-0.10376	0.0242

Note. This table shows the summary statistics for the second stage regressions of change in Amihud ILLIQ measure on comovement, measured as change in market beta for each stock. The change in ILLIQ is calculated as the log change in ILLIQ 180 days prior to and after inclusion. $\overline{\zeta_0}$ is the intercept, and $\overline{\zeta_1}$ is the slope coefficient on change in ILLIQ on comovement. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

there is excess comovement from index inclusion, then the volatility of the stock rises as a result of the stock inclusion. In the final period, $\Delta\beta$ is estimated at 0.2191, which results in an increased variance, the $abs(R_{it})$ in the ILLIQ calculation. This growth is in almost equal proportion to the growth in volume traded, and so the median change in the ILLIQ measure for the third period is just -3.65%.

There are two possible interpretations of this. Either the ILLIQ measure is correct, and the additions have in fact not become more liquid, or the Amihud ILLIQ measure is misspecified to analyse excess comovement, since any increase in excess comovement will be picked up as more illiquidity.

As we can not rule out the second possibility, we therefore perform two more tests to evaluate whether liquidity can explain excess comovement. In the first, we calculate the relative bid-ask spread for additions both prior to and following inclusion, and then examine whether the change in bid-ask spreads can explain changes in comovement. We calculate the relative bid-ask spread as $\frac{Ask-Bid}{Midpoint}$, and find that the average relative bid-ask spread drops 15.5% following inclusion. This is a sign that the stocks joining the OBX index are in fact becoming more liquid. But we run the same second-stage regression as before, and find absolutely no signs that this liquidity affects the comovement – every ζ_1 is indistinguishable from zero. The results are shown in Appendix C.

In the second test, we use insights from Næs et al. (2009), who found that liquidity is a priced risk factor on the Oslo Stock Exchange. Næs et al. (2009) construct a liquidity risk factor (LIQ) that is calculated as the returns of the most illiquid decile minus the returns of the most liquid decile on the OSEAX. This is a similar construction to the Fama and French (1993) SMB and HML factors. We use the LIQ factor to examine whether the stocks that joined the index, have increased their loading on the LIQ factor. We run the regression:

$$R_{it} = \eta_{0i} + \eta_{1i} R_{OBX,t} + \eta_{2i} LIQ + e_{it} \tag{23}$$

If the comovement can be explained by the inclusions changing their exposure to illiquidity risk, then η_2 should be different from zero. The null hypothesis is that the first assumption of our model holds – that inclusion is an information-free event, and that the effect of liquidity on comovement is therefore zero. Formally: $H_0 : \eta_2 = 0$. The results are shown in Table 9.

Table 9: Changes in loadings on OBX exposure and Liquidity exposure.

	$\overline{\eta_{1pre}}$	$\overline{\Delta\eta_1}$	$\overline{\eta_{2pre}}$	$\overline{\Delta\eta_2}$
1995–2018	0.94911***	0.08344**	0.13898**	0.0013178
1995–2002	1.0025***	0.0259	-0.0276	0.0197
2003–2008	0.9164***	0.0042	0.2816***	0.0568
2009–2018	0.919***	0.2304***	0.1923**	-0.0759

Note. This table shows the changes in loading on OBX and liquidity exposure from before to after inclusion. $\overline{\eta_{1pre}}$ is the average loading of OBX prior to joining. $\overline{\Delta\eta_1}$ is the average change in loading on OBX from before to after inclusion. $\overline{\eta_{2pre}}$ is the average exposure of liquidity prior to inclusion. $\overline{\Delta\eta_2}$ is the average change in exposure to liquidity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The change in exposure to the LIQ factor is not significant for any period, and is almost perfectly zero for the full sample. The estimate for $\Delta\eta_1$ is virtually identical to the estimate for $\Delta\beta$ from the single-factor model, for every time period. This test supports the null hypothesis that the inclusions have not changed their exposure to the liquidity risk factor.

We have in other words found that the cash value of volume traded strongly impacts the comovement of additions, but that this is likely not due to volume traded working as a proxy for liquidity. That is, however, hard to say definitively. Liquidity has several dimensions: the costliness of trading, how swiftly one may trade, and how much one may trade at one time. This is part of the reason there are many liquidity measures – no single one can pick up all of these dimensions (Næs et al., 2009). It is therefore still possible that volume traded picks up a dimension of liquidity that affects comovement, while the other three measures we have used, do not.

Regardless of what is the cause of volume traded affecting comovement, we must control for the change in volume traded that additions see. We have found strong indications that the single-factor model over-estimates the excess comovement, since part of the found excess comovement is in fact a result of increased volume traded.

6 Matched sample approach

Another way to test for whether the assumptions of comovement tests are broken, is to employ a matched sample approach. This is done by Barberis et al. (2005) and Chen et al. (2016) in the US, R. M. Greenwood and Sosner (2007) in Japan and Coakley et al.(2004) in the UK. The idea behind the test is to match inclusions with other stocks that saw a similar change in fundamentals, and then evaluate whether the inclusions saw different results than the sample. If the inclusions have a larger increase in fundamentals than the sample, one may conclude that there is excess comovement.

The importance of employing a matched sample approach was also recently highlighted by Grieser, William, Hoon, and Morad (2019), who found that comovement tests tend to overestimate excess comovement. Their findings indicate that there are latent factors in all stocks that result in any group of randomly selected stocks displaying excess comovement when employing the standard comovement tests. Any group cannot in reality see excess comovement, so this is a sign of miss-specified comovement tests. A solution is to consider the null hypothesis to be that the comovement should be equal to that of a randomly selected group, rather than zero. We therefore also create random samples and test comovement against those. In this section, we start to outline the empirical methodology for the matching tests, and then secondly present the results. We then proceed by analysing the result, and lastly perform a new test where we control for findings in the matching test.

6.1 Methodology

Creating a matching sample to interpret findings causally is challenging, and too little effort is often put into designing them (Stuart, 2010). The matching methodology must fit the data that is being examined. The number of stocks to potentially match with is substantially smaller in Norway than in countries where comovement researchers have previously used a matched sample approach. The majority of these researchers examined the US or UK. The US has over 4000 listed stocks, and the UK over 2000. In Norway, our sample has an average of 222 stocks per period. This puts significant restrictions on our ability to find good matches, and means that we have to put even more care into the construction of our matched samples than researchers in the US and UK do.

Ideally, the matched sample group should be as similar as possible as the treatment group along all dimensions – there should be no unobserved differences between the treatment and control group (Stuart, 2010). This is feasible in the US and UK where it is possible to match along several dimensions, such as firm size, momentum and industry, and still find good matches, but it is not feasible in Norway, where that would lead to either a very small matched sample, or one that is poorly matched along each dimension. We are therefore limited to testing only against a few dimensions at a time, and assume that unincluded control variables do not bias the result. To evaluate whether that assumption holds, we make samples for several different proxies for fundamentals that could feasibly affect comovement.

Variable selection based on estimated effects is a problem in matched samples, and researchers should therefore strive to select variables before observing the outcomes, basing the choice of variables on previous research as well as scientific understanding (Stuart, 2010). We therefore predefine 8 sets of metrics that we create 8 samples from, based on our findings in Section 5, and previous comovement tests. Five are based on our findings in volume traded and liquidity:

1. Total Volume traded before and total volume traded after
2. Change in volume traded before and after
3. Change in volume traded before and after, as well as total volume traded before
4. Change in Amihud before and after

5. Change in relative spread before and after

Three are based on Chen et al. (2016) and Barberis et al. (2005)

6. Firm size

7. Momentum before and after

8. Momentum and firm size

Since our group to select sample stocks from is small, we consider it unlikely that most stocks have several good matches, and select only one match for each inclusion. We therefore employ a method similar to nearest neighbour matching (Stuart, 2010). To find which stock is the closest match, we combine the matching methodology of Barberis et al. (2005) with the loss function from macroeconomic policy.

Concretely, the process for choosing the nearest match is as follows: We calculate each metric for every stock on Oslo Børs that has sufficient data, and is not on the OBX index either prior to or following rebalancing. We then sort all those stocks in ascending order, and calculate how many percent of them each inclusion is larger than. This provides us with a percentile for each metric for each inclusion. We then pick the closest match as the one that has the lowest sum of the squared differences in percentiles. That is, the one that minimises the following loss function:

$$Loss_s = \sum_{m=1}^{N} (Percentile_{mi} - Percentile_{ms})^2 \tag{24}$$

where $Percentile_{mi}$ is the percentile of inclusion i for metric m, and $Percentile_{ms}$ is the percentile of potential sample stock s for metric m. N represents the total amount of metrics used. The closest match is in other words the one that minimises the squared sum of deviance in percentiles.

For each of the 8 samples, we evaluate whether the sample provides meaningful information about the inclusions that they match, by running a two-stage regression. In the first stage, we repeat the single-factor model with the sample return as the response variable: $R_{Sample,t} = \beta_0 + \beta_{Sample} * R_{OBX,t} + e_t$. We then calculate $\Delta\beta_{Sample}$ and use this in a second-stage regression in the shape of:

$$\Delta\beta_{Inclusions} = \alpha_0 + \alpha_1 \Delta\beta_{Sample} + e \tag{25}$$

where α_1 then shows the extent to which the change in comovement for the sample stock has explanatory power for the change in comovement on the actual inclusion that it is matched with. If the metrics we are matching along cause comovement, then we would expect α_1 to be positive. If the metrics do not cause comovement, however, then α_1 should then be zero. Formally, the null hypothesis is: $H_0\colon \alpha_1 = 0$

Per the criticism of Grieser et al. (2019), we also create three samples consisting of randomly selected stocks.

6.2 Results

Table 10 shows the results of the second-stage regression for each of the 11 samples.

Table 10: Second-stage regression

Metrics used to matched along	$\overline{\alpha_0}$	$\overline{\alpha_1}$	Adjusted R^2
Volume traded pre and post	0.06833**	0.088	-0.0011
Δ Volume Traded pre and post	0.077507**	0.32774***	0.125
Δ V. traded pre/post and tot V. Pre	0.08909**	0.3744***	0.1317
Δ Amihud ILLIQ	0.070501**	0.086	-0.0002
Δ Bid-Ask Spread	0.068662**	-0.105	0.0009
Firm Size	0.067928**	0.14714	0.00741
Momentum Pre and Momentum Post	0.070866**	0.026332	-0.00632
Firm size and Momentum Pre + Post	0.067026**	0.20308**	0.0324
Random sample 1	0.06216*	0.10214	0.00247
Random sample 2	0.071385**	-0.012455	-0.00813
Random sample 3	0.076149**	0.0033795	-0.00794

Note. This table shows the results of each second stage regression run on the eight samples presented in Section 6.1. α_1 shows the slope in a regression with the $\Delta\beta$ of the sample as the explanatory variable, and the $\Delta\beta$ of the OBX inclusions as the response variable. It shows the extent to which the change in comovement for the matched sample has explanatory power on the change in comovement of the comovement of OBX inclusions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The null hypothesis is rejected for three of the samples: The two involving the change in volume traded, and the one based on firm-size and momentum. These results are mostly in line with our findings in Section 5: Change in volume traded and change in $\Delta\beta$ are related. The difference from our findings in 5 is that firm size and momentum is indicated to have an effect, while we found the opposite previously.

The Adjusted R^2 here tells us about the economic magnitude of the metrics. It shows how large a share of the change in the $\Delta\beta$ of the OBX inclusions can be explained by the change in their matched stocks. The only way we have reason to believe the $\Delta\beta$ of the inclusion and matched sample are systematically related, is through similarity in the metrics matched along. A high R^2 thus signals that the metric matters for comovement. The found adjusted R^2 of 12.5% and 13.17% for the two samples with change in volume traded is high, and of an entirely different magnitude than all other samples.

Figures 8, 9 and 10 show how the three samples' (samples 2, 3 and 8) delta betas move over time.

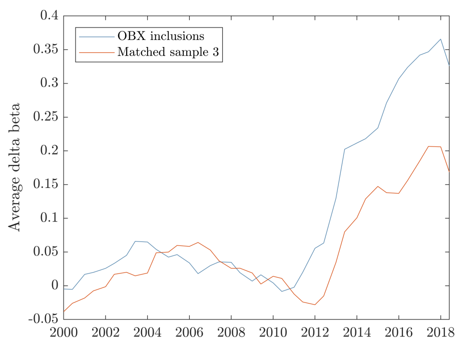


Figure 8: Sample matched on total volume and change in volume (sample 3)

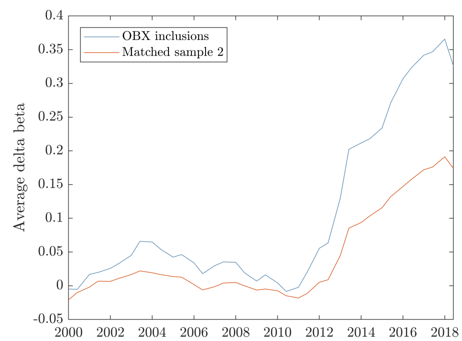


Figure 9: Sample matched on change in volume (sample 2)

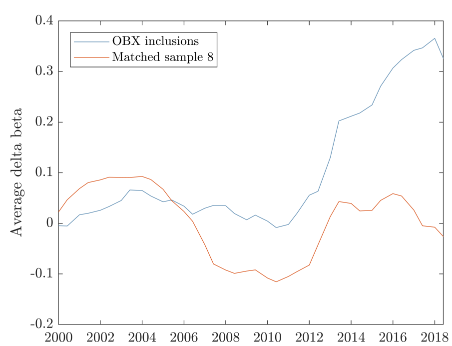


Figure 10: Sample matched on firm size and momentum (sample 8)

The two volume-traded samples display movements in $\Delta\beta$ that are quite close to the stocks they match. The momentum based sample displays some similarities, but not as strong ones. This is a very similar result to that found in Section 5 – the only variable that we find strongly affects the comovement of OBX inclusions is volume traded.

6.3 Analysing the effect of volume on comovement

We have established through several tests that volume traded affects stock comovement. This breaks assumption 1 in Section 4.2 of the single-factor model, that stock inclusion is an information-free event, and therefore independent of changes in fundamentals. The results of the single-factor model are therefore likely biased, since the $\Delta\beta$ appears to pick up two separate effects: the excess comovement effect, and the increased comovement from increased volume traded. We need to devise a test to separate the two effects, and to do that, we need to understand more about how volume traded affects comovement, and how that effect differs from excess comovement due to index inclusion.

To examine this, we run the single-factor model with the non-OBX index as the explanatory variable. Our hypothesis is that volume traded affects comovement with the non-OBX index differently than being included on the OBX index does. We run the following regression:

$$R_{it} = \alpha_i + \eta_i R_{Non,t} + \epsilon_{it} \tag{26}$$

where $R_{non,t}$ is the return of the non-OBX index on day t. We defined the non-OBX index as the value-weighted return of all OSEAX stocks that are not on the OBX index. We run this regression for both the actual OBX inclusions, and for the three matched samples from the previous section. We then compare the coefficient $\Delta\eta_i$ with the $\Delta\beta_i$ found from running the regression with OBX as the explanatory variable ($R_{it} = \alpha + \beta_i R_{OBX,t} + \epsilon_{it}$).

Per our model, the OBX inclusions see increased $\Delta\beta$ after joining due to being exposed to OBX-specific shocks S_{OBX}, and no longer being exposed to S_{Non} (provided shocks to non-OBX stocks exist). That is not the case with the matched sample stocks – their exposure to S_{OBX} and S_{Non} is unchanged.

Our hypothesis is therefore that for OBX inclusions, $\overline{\Delta\beta} > \overline{\Delta\eta}$, due to increased exposure to S_{OBX}. For the matched samples, we by the same reason expect that $\overline{\Delta\beta} =$

$\overline{\Delta\eta}$. We present the results for $\Delta\beta$ and $\Delta\eta$ in Table 11.

Table 11: Effect of volume on comovement

	Results for the full period	
	$\overline{\Delta\beta}$	$\overline{\Delta\eta}$
OBX Inclusions	0.0720***	0.0108
Sample 2	0.0437*	0.0703**
Sample 3	0.0536*	0.0654*
Sample 8	0.0279	0.0403
	Results after 2009	
	$\overline{\Delta\beta}$	$\overline{\Delta\eta}$
OBX Inclusions	0.2191***	0.1296**
Sample 2	0.1410**	0.1712**
Sample 3	0.1199*	0.0987*
Sample 8	0.0267	0.0189

Note. This table shows the slope coefficient of the four sets of stocks against the OBX index and non-OBX index. The regressions are run independently, and $\Delta\beta$ is the slope against the OBX index, while $\Delta\eta$ is the slope against the non-OBX index. Sample 2 is created by finding the best match with regards to the change in volume traded prior to and following inclusion. Sample 3 matches along those two dimensions, as well as total volume traded. Sample 8 matches on firm size as well as momentum before and after inclusion. Standard errors for $\Delta\beta$ and $\Delta\eta$ are heteroskedasticity robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The OBX inclusions see a substantially larger increase in comovement with the OBX index than it does with the non-OBX index. For the three samples, however, $\Delta\beta$ is either smaller than or approximately the same size as $\Delta\beta$. These results indicate that the comovement of inclusions is different from that of the sample stocks. While the samples see a general increase in comovement with both the OBX and the non-OBX, the OBX inclusions experience a far higher increase in comovement with the OBX index than the non-OBX index. This indicates that there is excess comovement from OBX membership. To verify whether this is the case, we employ tests to establish a causal effect in Section 6.4.

Before we proceed to test that relation, we comment on the $\Delta\eta$ for OBX inclusions. After 2009, the $\Delta\eta$ is positive and large for the OBX inclusions. Our model cannot explain this increase being a result of excess comovement from index membership, so it must stem from another source. The $\Delta\eta$ is similar in magnitude to that of the two samples matched based on volume traded. Recall our findings in Section 5.5 that volume traded causes comovement with the OBX to increase for all stocks. This test has a similar implication: increased volume traded increases comovement with both the OBX and non-OBX indexes. Excess comovement from index membership, however, should according to our model only increase comovement only with the OBX index.

6.4 Test for excess comovement after controlling for volume traded

We now have three samples which have similar changes in volume traded, but in which only one was included on the OBX index. In this section, we employ a test suggested by Stuart (2010) for using matched samples to estimate causal effects. This type of test entails using index inclusion as a treatment effect, and the matched samples as the counter-factual stocks that did not receive treatment. Formally, we run the regression:

$$\Delta\beta_i = \alpha_0 + \alpha_1 I_i + \alpha_2 * \Delta Volume_{i,Pre} + \alpha_3 * \Delta Volume_{i,Post} + e_i \qquad (27)$$

where $\Delta\beta$ comes from the single-factor model, $\Delta Volume_{Pre}$ is the log change in volume over the period prior to inclusion, and I is a dummy that takes the value of one if the stock is an OBX inclusion, and zero if it is a sample stock. α_1 tells us how much higher the increase in comovement is for the inclusion than the sample stocks, after controlling for changes in volume traded.

Our null hypothesis is that fundamentals explain everything, and that α_1 is therefore zero. Our alternative hypothesis is that there is excess comovement from index membership. Formally: $H_0 : \alpha_1 = 0$ vs. $H_1 : \alpha_1 \neq 0$. The results of the regression are shown in Table 12.

After 2009, the α_1 is estimated to 0.144. This is an estimate for the amount of comovement left after controlling for increased volume traded. This is a reduction from 0.2191 that we found in the single-factor model, which did not control for volume traded. The remaining 0.0751 are attributable to the increase in volume traded. The conclusion from this matched samples approach, is therefore that there is excess comovement in the Norwegian stock market after controlling changes in volume traded.

It is worth commenting on the limitations of this result. It relies on the matched

Table 12: Excess comovement after controlling for volume traded

	α_0	α_1	α_2	α_3
1995–2018	-0.029489	0.085111**	0.068638***	0.1050***
1995–2002	-0.06428*	0.091016*	0.006976	0.099145**
2003–2008	-0.026053	0.052688	0.020797	0.13254**
2009–2018	-0.006068	0.14384**	0.12821**	0.17978**

Note. This table presents the results from testing excess comovement after controlling for volume traded divided into different sub-periods.The variable of interest, α_1 signals how much higher the increase in comovement is for the inclusion than the sample stocks, after controlling for changes in volume traded. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

samples being sufficiently good matches for the inclusions. We have attempted to be as thorough as possible in the matching process, but the Norwegian stock market is small, and the matches are therefore not perfect. That is a potential limitation of these results. We therefore employ an alternative model in Section 7, to verify these results, and further establish causality.

7 Alternative model

7.1 Regression discontinuity model

In the thesis so far, we have covered that volume traded has a strong effect on the β towards the OBX index, and that this biases the original single-factor model. We have employed a test to control for this volume effect, by using matched samples, and found results indicating that there is excess comovement after controlling for volume traded. That test hinges on the assumption that the samples are representative matches of the inclusions, however. If there is a systematic difference between the samples and the OBX inclusions, apart from index inclusion, then we may have biased results. We therefore create another test which does not rely on matched samples, to verify the results previously found.

This test is a regression discontinuity design, using an instrumental variable approach. This is a variation of a test employed by Boyer (2011), modified to fit studying the OBX.

In an ideal regression discontinuity design, subjects are separated into two groups: one that receives a treatment, and one that does not. There is a clearly defined cutoff point. Above that point, treatment will be given. The cutoff point on volume traded to join the OBX index is not as perfectly defined – the constituents of the OBX are not always the top 25 stocks we have calculated as most traded in the calculation period. Oslo Børs uses some discretion in choosing the constituents, caring not only about volume traded, but also about OBX to some extent representing the full OSEAX (Oslo Børs, 2018).

To overcome this problem, we use entering the top 25 most traded stocks as an instrument, and calculate the probability of being included in the OBX by passing this cutoff. We run the following OLS regressions in a two-stage least square (2SLS) setting:

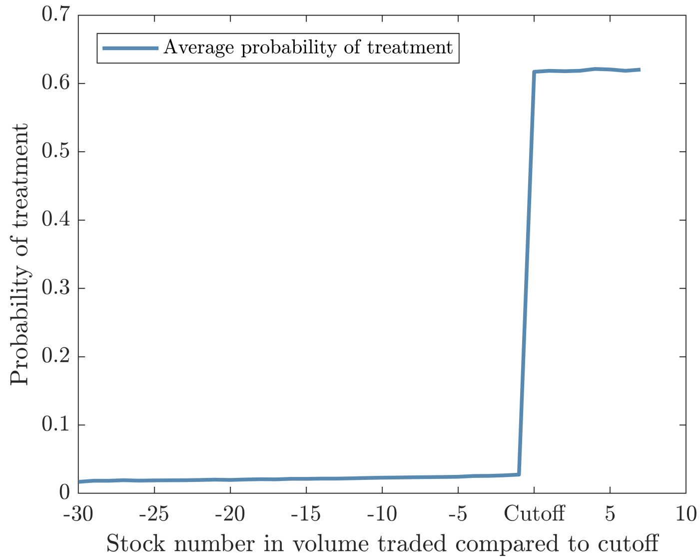
$$T_i = \eta_0 + \eta_1 * log(V_i) + \eta_2 * log(MV_i) + \eta_3 * D_i + e_i \tag{28}$$

where T_i is equal to one if the stock was included in the OBX index after rebalancing, and zero if the stock was not. V_i is the cash value of volume traded for the stock over the six months prior to rebalancing. MV_i is the market value of firm i on the day before rebalancing. Since the market values and volume traded differ between periods, we standardise these to have the same average in every period. D_i is a dummy variable that takes the value of one if the stock is in the top 25 most traded stocks on the index, and zero otherwise, and η_3 then shows the expected increase in the probability of treatment. For each rebalancing, the test is run for the 50 most traded stocks on the OSEAX index that were not on the OBX index in the period before rebalancing.

The results are presented in Panel A of Table 13. Increased volume traded and increased firm size lead to a larger probability of inclusion, but the largest effect comes from being in the top 25, which increases the probability by approximately 59$\%$. This is illustrated in Figure 11. An increase of 59$\%$ is enough variation caused by something that is quasi-random to run a second-stage OLS regression discontinuity design regression. The increase being only just 59$\%$ will mean that the hit-rate of prediction is far from perfect. This will not bias the regression results, but may lead to high standard errors (Boyer, 2011).

In the second stage regression, we try to determine how much receiving treatment

Figure 11: Estimated probability of treatment (being included in the OBX) based on distance to cutoff



Note. This graph shows the probability of inclusion based on distance from the cutoff. The X-axis represents stocks listed by total value traded, where stock Cutoff is the stock with the highest value traded that would not get in if index inclusion were only determined by value traded. Stock cutoff + 1 is the stock with the lowest turnover of those that would get in.

affects the comovement with the OBX index. The measure for comovement is the β_1 in a standard OLS regression in the shape of $R_i = \beta_0 + \beta_1 * R_{OBX} + e_i$. The second stage regression is formally:

$$\beta_{1i} = \theta_0 + \theta_1 * log(V_i) + \theta_2 * log(MV_i) + \theta_3 * T_i + e_i \tag{29}$$

where θ_3 is the estimate of how much an increase in the expected probability of treatment affects the comovement of stock i. This regression discontinuity model works as a quasi-randomised experiment. The difference in volume traded is picked up through θ_1.

The null hypothesis of the test is that fundamentals alone explain the β_i, and in other words that θ_2 is equal to zero. Formally: $H_0 \colon \theta_2 = 0$. The alternative hypothesis is that there is excess comovement from index membership, even after this model controlling for the level of volume traded. The results of the regression are shown in Panel B of Table 13.

These results add support for the alternative hypothesis – that there is excess comovement after controlling for volume traded – after 2009. This result is similar to that

Table 13: Results of regression discontinuity design

	Panel A: First stage regression		
	η_1	η_2	η_3
Full period	0.004773***	0.0015921***	0.58932***
	Panel B: Second stage regression		
	θ_1	θ_2	θ_3
1995–2018	0.2263***	-0.14125***	0.16623**
1995–2002	0.22151***	-0,1768***	0.0099
2003–2008	0.28183***	-0.11676***	0.11053
2009–2018	0.24065***	-0.12952***	0.26557**

Note. The first stage regression is an estimate of how much the probability of inclusion to the OBX is affected by the log of cash value of volume traded (η_1), log of market capitalisation (η_2), and being in the top 25 most traded stocks (η_3). The second stage regression shows how much the estimated change in comovement due to log of cash value of volume traded (θ_1), log of market capitalisation (θ_2), and estimated probability of inclusion to the OBX, as calculated by the first-stage regression (θ_3).

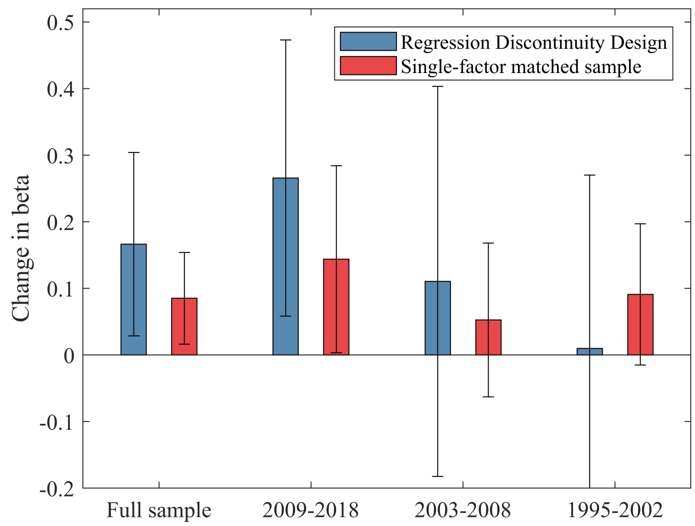
found with the single-factor and two-factor models.

There is an indication of comovement in the 2003-2008 period, as well, with a θ_3 of 0.11053, but it is not statistically significant. In the 1995-2002 period, θ_3 is virtually zero. The θ_3 is in other words growing over time, similar to what we saw the $\Delta\beta$ do in the main tests.

It is worth noting the high θ_1 and the highly negative θ_2. Market value and total volume traded are highly correlated, so it is important to keep in mind that these coefficients are the effect of changing one and holding the other constant. If total turnover is not included in the model, the effect of market value becomes positive. The effect is simply dominated by the total turnover effect. This is a similar effect as we saw in the model using the Carhart four-factor model, where loading on SMB increased for additions when OBX was included, but fell if the regression was run without OBX. We consider this another piece of information supporting the idea that volume traded matters more than firm size and momentum for comovement on Oslo Børs.

As a robustness test, we also run this test with the Carhart four-factor model as the response variable in the second-stage regression. We do this to ensure that the θ_3

Figure 12: Estimates and uncertainty of RDD and Single factor model



Note. This plot shows the estimates from the Regression Discontinuity Design and the single-factor regression, along with their 95% confidence interval. Both are controlling for changes in volume traded.

found in this test doesn't pick up changes in other fundamentals. Formally, the response variable is the β_1 from $R_{it} = \beta_0 + \beta_1 R_{OBX} + \beta_2 SMB + \beta_3 HML + \beta_4 PR1YR + e_{it}$. The results of the second-stage regression is, in terms of statistical significance, identical with respect to θ_3: Significant for the full period and the last, not for the other two. This reinforces our belief that the assumptions underlying this regression discontinuity design hold.

The betas found in the regression discontinuity design are comparable to those in the main single-factor model. We illustrate the results of the regression in the following graph, where we compare it to the original univariate regression.

We have now compared three different tests which control for changes in volume traded, and find excess comovement after controlling for those.

8 Robustness testing

To ensure the results in this thesis are reliable, we perform several robustness tests. This section is organised as follows: First, we test how index deletion affects comovement. Secondly, we employ another commonly used comovement test: a two-factor regression including non-OBX as an explanatory variable.Then, we test whether stock inclusions see increased variance, as our model predicts. Fourthly, we use the high share of energy stocks as an instrument, and test for whether inclusions see increased comovement with the energy sector. Finally, we present an analysis of whether the assumption of independence among inclusions holds.

8.1 Index removals

In the main part of this thesis, we studied exclusively the stocks that were included on the OBX index. For every stock that was included, however, there is another which was removed from the index. The stocks that were removed from the index should by our model see the opposite effect of what inclusions do. Prior to removal, the stock is an OBX stock, and exposed to OBX shocks. Following removal, it is a non-OBX stock, and exposed to non-OBX shocks instead. This is the precise mirror of the OBX inclusions. If we run the single-factor regression,[7] $R_{Removal,t} = \beta_0 + \beta_{Removal} R_{OBX,t} + e_t$ on the index removals, our model then predicts that the $\Delta\beta$ of the deleted stocks will be equal to the exact opposite of the $\Delta\beta$ from the regression run for the index inclusions:

$$\Delta\beta_{Removal} = -\frac{\gamma^{OBX}_{Removal} * \sigma^2_{S_{OBX}}}{\sigma^2_{OBX}} \tag{30}$$

The results of that regression for the 104 removals with sufficient data, are shown in Table 14, and plotted over time in Figure 13. The results for the full period are similar to that of the inclusions, but with a slightly larger magnitude. The time-trend is different, however, with the $\Delta\beta$ having the magnitude in the last 2003–2008 period and the 2009–2019 period.

As with the inclusions, this test assumes that index removal is an information-free event, which is not necessarily the case. We therefore repeat our tests for breaches of fundamentals. In the interest of brevity, we do not report every result, but instead present the takeaways.

Removals have a slight tendency to be non-momentum stocks prior to deletion, having a median reduction in market value of 7% over the six months prior to deletion.

[7] Since the deletion is a member of the OBX prior to removal, and therefore a part of the X-variable, we exclude the stock from the OBX prior to inclusion. This is the same procedure as we outline in Appendix A for inclusions.

Table 14: Effects of removal from OBX

	$\overline{\Delta\beta}$	SE($\overline{\Delta\beta}$)	tStat
1995–2018	-0.0948	0.0279	-3.3978
1995–2002	-0.0556	0.0400	-1.3907
2003–2008	-0.1129	0.0522	-2.1643
2009–2018	-0.1159	0.0645	-1.797

Note. This table reports the summary statistic of the effect of index deletion for the different time periods. It is calculated by regressing the stocks' return on the OBX-return prior to and following index deletion. $\overline{\Delta\beta}$ is the average change in beta, SE is the heteroskedasticity robust standard error, tStat is the variable test statistic, and Δ R^2 is the change in variation explained by OBX-return. The sample size n =104.

Following deletion, they show no trend, with a median growth of 1%.

Volume traded falls both prior to deletion and after, with a drop of 19.55% prior to deletion, and a drop of 15.96% after. Liquidity is found to be adversely affected by using the Amihud and bid-ask spread. The bid-ask spread increases by 5% in the period before removal, and by 35.28% after. The Amihud measure rises by 46% before, and 35% after for the median deletion.

Running the tests from Section 5, momentum is not shown to have any effect for removals. Neither is proxies for fundamentals, industry, the bid-ask spread, the Amihud ILLIQ measure, nor non-synchronous trading.

Volume traded, however, matters for removals. As with the inclusions, we run the regression:

$$\Delta\beta_{Removal} = \zeta_0 + \zeta_1 * log\frac{V_i^a}{V_i^b} + e_i \tag{31}$$

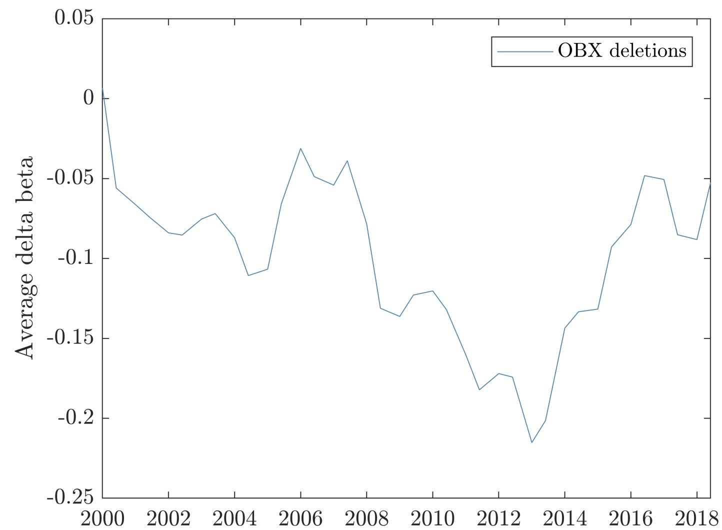
where the $\Delta\beta_{Removal}$ stems from the single-factor regression, and $log(\frac{V_i^a}{V_i^b})$ is the change in volume traded from prior to deletion to after.

The results of the regression are reported in Table 15. They show a very similar trend as volume traded did for inclusions, with the exception that ζ_1 and R^2 are lower in the final period than the middle one.

Overall, we see that removals from the OBX index tend to see decreased volume traded, and that decreased volume traded will lower the betas. We therefore control for changes in volume traded.

We perform the matched sample test again, finding matches on volume traded for the deletions in the same procedure as we did with the inclusions. We create samples

Figure 13: Five-year average delta beta over time for deletions



Note. This graph shows the 5-year running average change in beta from before deletions to after deletions, over the five years prior to the data point. As an example, the data point in 2008 is the average delta beta between January 2004 and January 2008.

by matching along the two sets of metrics that mattered for inclusions. That is, one sample matching on the change in volume traded prior to and post rebalancing, and one sample matching on both of those as well as the total volume traded.

We then perform the regression of Section 6.4, with the index deletions and their matched samples. That is, we first calculate the $\Delta\beta$ of both the deletions and their matched samples, and then run the following second-stage regression:

$$\Delta\beta_i = \alpha_0 + \alpha_1 I_i + \alpha_2 * \Delta Volume_{i,Pre} + \alpha_3 * \Delta Volume_{i,Post} + e_i \qquad (32)$$

The results of the second-stage regression are shown in Table 16. The α_1 coefficient shows the estimate for the change in comovement after controlling for changes in volume traded. For the full period, the α_1 is -0.0690, and significant at the 10% level. This is remarkably similar to having the opposite sign of the α_1 found for inclusions, which was +0.07203. In the final period, the α_1 is +0.14384 for the additions, and -0.1293 for the removals. This signals the same economic magnitude, but the results for the deletions are not significant at the 5% level for any period. Figure 14 presents a graphical comparison of the results of the deletions and the inclusions. The general similarity provides strong support for the findings in the main part of this thesis. Joining the OBX

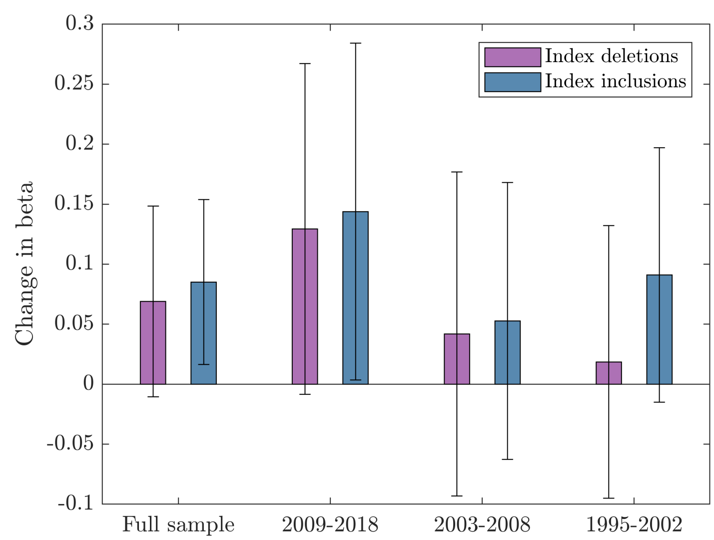
Table 15: Regression of change in volume traded on comovement for OBX deletions

	ζ_0	ζ_1	R^2
1995–2018	-0.071882**	0.1109**	0.0397
1995–2002	-0.090964*	0.059194	0.0265
2003–2008	-0.0042856	0.2374*	0.112
2009–2018	-0.092143	0.17369	0.0507

Note. This table presents the effect of the loading on change in traded volume on change in beta for each specific index deletion, divided into different time periods. ζ_0 is the intercept and ζ_1 is the slope coefficient. R^2 signals the variation explained by the model. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

index causes the stock to be exposed to group-specific shocks, and therefore display excess comovement. Leaving the index causes the stock to lose those same shocks, and therefore causes a similarly sized drop in comovement.

Figure 14: Comparison of estimates of excess comovement found in tests of inclusions and deletions



Note. This figure shows the estimates for comovement from OBX membership, found by examining index inclusions and index deletions. For both, the results are the excess comovement found after employing a matched sample approach to control for changes in volume traded. The change in beta of the index deletions is multiplied by -1 to make them show the same economic magnitude as the index inclusions do.

Table 16: Change in comovement for removals from index after controlling for volume traded

	α_0	α_1	α_2	α_3
1995–2019	0.0154	-0.069037*	0.055827*	0.089929**
1995–2002	-0.02351	-0.01855	0.07773**	0.13215***
2003–2008	0.02041	-0.04182	0.082651	0.22785**
2009–2019	0.071538	-0.12932*	0.1081*	0.027656

Note. This table presents the results from testing excess comovement for removals after controlling for volume traded. The variable of interest, α_1 signals how much lower the decrease in comovement is for the removal than the matched sample stocks. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

8.2 Two-factor model accounting for changes in fundamentals

A second commonly used model in the comovement literature is a bivariate regression. Stocks added to an index are regressed not only on the index it joins, but also on the index it leaves. Barberis et al. (2005) was the first to employ it in a comovement setting, and ran the regression $R_{it} = \alpha + \beta_{1i} * R_{S\&P,it} + \beta_{2i} * R_{non-S\&P,it} + e_{it}$, where non-S&P 500 is the value-weighted return of all stocks that could join the S&P 500 index. He found a β_1 in this regression of a far higher magnitude than in the single-factor model.

The test has since been used by several other authors, and been used as proof of comovement. For instance, Coakley et al. (2004) ran the regression $R_{it} = \alpha_i + \beta_{1i} * R_{FTSE,it} + \beta_2 * R_{non-FTSE,it} + e_{it}$, where non-FTSE is all stocks on the FTSE all-share index that are not in the FTSE 100 index. He considered that he controlled for non-FTSE return by running this bivariate regression, and found a considerably higher $\Delta\beta_1$ estimate in the bivariate than univariate regression.

Chen et al. (2016) provide strong criticism of the previous use of the bivariate regression. He proves that while the β_1 is higher in the bivariate regression, it does not actually provide any meaningful information about the economic magnitude of comovement. For this reason, we derive how to interpret the coefficients in the bivariate regression in our model in Appendix D.

We run the following regression:

$$R_{it} = \alpha_i + \beta_{1i} R_{OBX,t} + \beta_{2i} R_{Non,t} + \epsilon_{it} \tag{33}$$

where R_{Non} is the return of the non-OBX index, and R_{OBX} is the return of the OBX index, excluding stock i from the index after inclusion.

Under the same assumptions as in our initial model, the expected value of $\Delta\beta_1$ and $\Delta\beta_2$ for inclusions to the OBX are derived to be:

$$\Delta\beta_{1i} = \frac{\gamma_i^{a,OBX} * \sigma^2_{S_{OBX}} * \sigma^2_{NON} + \gamma_i^{b,NON}\sigma^2_{S_{NON}} * cov(OBX, NON)}{\sigma^2_{OBX} * \sigma^2_{NON} - cov(OBX, NON)^2} \tag{34}$$

$$\Delta\beta_{2i} = \frac{-(\gamma_i^{a,OBX} * \sigma^2_{S_{OBX}} * cov(OBX, NON) + \gamma_i^{b,Non}\sigma^2_{S_{NON}} * \sigma^2_{OBX})}{\sigma^2_{OBX} * \sigma^2_{NON} - cov(OBX, NON)^2} \tag{35}$$

where $\gamma_i^{a,OBX}$ is the loading of stock i on shocks S_{OBX} after inclusion, $\sigma^2_{S_{OBX}}$ is the variance of those shocks, $\sigma^2_{S_{OBX}}$ the variance of the OBX index, and cov(OBX, NON) is the covariance between the OBX and non-OBX indexes.

The two $\Delta\beta$s are caused by the shocks to OBX and non-OBX – in the absence of shocks, both $\Delta\beta_1$ and $\Delta\beta_2$ would be theorised to be zero. The null hypothesis is therefore that $\Delta\beta_1$ and $\Delta\beta_2$ are each zero, while the alternative hypothesis is group-specific shocks cause $\Delta\beta_1$ to be positive, and $\Delta\beta_2$ to be negative.

The results of the first-round regression for the full period and for the period after 2009 are shown in Table 17. Included are the results of the bivariate regression for the two volume-traded based matched samples.

Table 17: Result from the two-factor model

	Full period		After 2009	
	$\overline{\Delta\beta_1}$	$\overline{\Delta\beta_2}$	$\overline{\Delta\beta_1}$	$\overline{\Delta\beta_2}$
OBX Inclusions	0.1773***	-0.1445**	0.2571***	-0.0805
Sample 2 (Δ Volume Traded pre and post)	0.0099	0.0832*	0.0562	0.18733*
Sample 3 (Δ V. traded pre/post and tot V. Pre)	0.0245	0.0314	0.08466*	0.00265

Note. This table shows the results of the bivariate regression for the OBX inclusions, and the two volume-traded based matched samples. $\Delta\beta_1$ is the loading on the OBX index, and $\Delta\beta_2$ is the loading on the non-OBX index. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

$\Delta\beta_1$ and $\Delta\beta_2$ of the sample stocks have the same sign, and similar magnitude. For the OBX inclusions $\Delta\beta_1$ is strongly positive, and $\Delta\beta_2$ strongly negative for the full period. This is what our model predicts, since the exogenous shocks S_{OBX} and S_{NON} push β_1 upward, and β_2 downward. In the after 2009 period, however, $\Delta\beta_2$ is not significantly negative. We know from the earlier tests in Section 6.3 that volume traded affects the comovement of the inclusions in the final period, pushing the comovement with both the OBX and non-OBX indexes up. We therefore perform a second-stage regression to control for the changes in volume traded, by comparing the changes in comovement with that of our matched sample.

We repeat the bivariate regression for the two volume based matched samples, and use these to calculate the effect of treatment. That is, we run:

$$\Delta\beta_i = \alpha_0 + \alpha_1 I_i + \alpha_2 * \Delta Volume_{i,Pre} + \alpha_3 * \Delta Volume_{i,Post} + e_i \tag{36}$$

where I_i is one if stock i is one of the inclusions, and 0 if it is a sample stock. α_1 is therefore a measure of the $\Delta\beta$ after controlling for changes in volume traded.

We run the second-stage regression separately with $\Delta\beta_1$ and $\Delta\beta_2$ as response variables. With $\Delta\beta_1$ as the response variable, our model predicts that α_1 is positive and significant, and with $\Delta\beta_2$ that α_1 is negative.

The results of the regression are reported in Table 18. α_1 is highly positive with $\Delta\beta_{1Inc}$ as the response variable, and highly negative with $\Delta\beta_{2Inc}$ as the response variable The two α_1s are of similar magnitude, but opposite signs, which is precisely what the alternative hypothesis suggested. This therefore strongly supports our main findings that there are exogenous shocks to the OBX and non-OBX indexes.

But as Chen et al. (2016) suggest, these variables do not carry much economic meaning. They are most definitively not directly comparable to the $\Delta\beta$ of the single-factor regression, which has economic meaning, and we therefore consider the results of this subsection to simply add support to our main findings.

8.3 Excess comovement and variance

Grieser et al. (2019) point out that normal tests of comovement overestimate the extent to which there is comovement. They pose that a better way to examine the existence of excess comovement is through variance ratios. The idea is that if one group has excess comovement, then that group should also have higher variance than a group with no

Table 18: Second stage regression to estimate the effect of index inclusion on delta beta 1 and delta beta 2

	Delta beta 1 as response variable			
	α_0	α_1	α_2	α_3
Full period	0.01551	0.13978***	0.0335**	0.0092296
After 2009	0.03895	0.28735***	0.04297	0.068709
	Delta beta 2 as response variable			
	α_0	α_1	α_2	α_3
Full period	0.02454	-0.15102***	0.00471	0.0429
After 2009	0.08323	-0.32141***	0.0189	0.0248

Note. This table presents the results of a second-stage regression to estimate the change in $\Delta\beta_1$ and $\Delta\beta_2$ of the two-factor regression, after controlling for volume traded. The variable of interest, α_1 signals how large the response variable is after controlling for volume traded. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

excess comovement.

This notion also makes sense for our single-factor model: We derived our measure for excess comovement as the percent of variance on the OBX resulting from group-specific shocks: $\Delta\beta_i = \frac{\gamma_i^{OBX} * \sigma_{S_{OBX}}^2}{\sigma_{OBX}^2}$. If there truly are group-specific shocks, then the variance of stocks exposed to the shocks should increase.

We test this by examining whether the variance of OBX inclusions increase after inclusion: σ_i^a/σ_i^b.

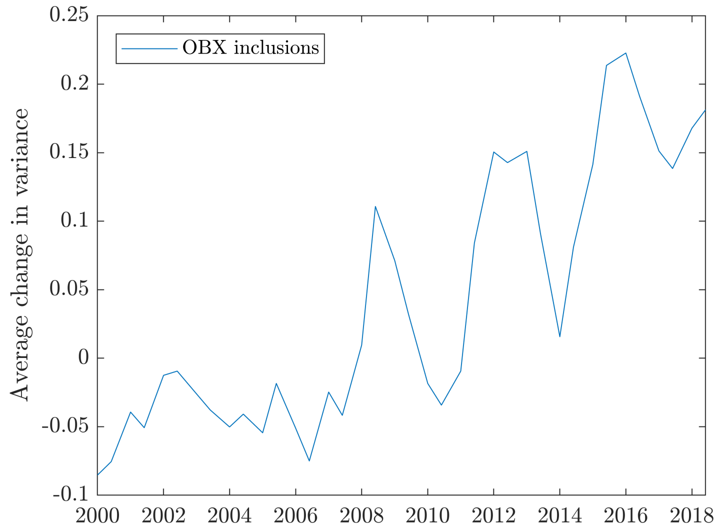
We cannot merely test for whether this ratio increases, however. The variance of stocks on the OBX varies strongly over time – there are low-volatility periods and high-volatility periods.[8] Stocks added to the OBX in June 2008 saw a dramatic increase in their variance, but that was not due to OBX inclusion, it was due to the financial crisis. We therefore see how much more the OBX inclusions variance has increased compared to the variance of the OSEAX index. We calculate:

$$\Delta Variance_{inc} = log\left(\frac{\sigma_{inc}^{2,a}}{\sigma_{inc}^{2,b}}\right) - log\left(\frac{\sigma_{OSEAX}^{2,a}}{\sigma_{OSEAX}^{2,b}}\right) \tag{37}$$

where $\sigma_{inc}^{2,a}$ is the variance of inclusion inc in the period after inclusion. $\Delta Variance_{inc}$

[8]See Figure B1 in Appendix B for a breakdown of how OBX variance has changed over time.

Figure 15: Five-year average change in variance over time



Note. This graph shows the five-year average change in variance over time. As an example, the data point in 2008 is the average change in variance between January 2004 and January 2008.

signals how much more the inclusion varies after inclusion, than it would have had the stock not been included, assuming its trend would have been the same as that of the OSEAX index. This is shown in Figure 15.

This provides a similar viewpoint as the single-factor model gave, but a slightly weaker result. The results by period are shown in Table 19.

Table 19: Increase in variance from OBX inclusion

	$\overline{\Delta Variance}$
1995–2018	0.0364
1995–2002	0.0174
2003–2008	-0.0189
2009–2018	0.0882

Note. This table shows the results of a regression to determine whether index inclusions see a larger increase in variance than other stocks do. ($\overline{\Delta Variance}$) is calculated as the change in the variance of the inclusion, subtracting the change in the variance of the OSEAX.

We see that the variance increase presents a similar trend to the $\Delta\beta$s: around zero in the first two periods, and higher and positive in the final.

What we are primarily interested in, is seeing whether excess comovement results in increased variance. We therefore use our estimate for $\Delta Variance$ and run a second-stage regression in the shape of:

$$\Delta Variance_i = \alpha_0 + \alpha_1 * \Delta\beta_i + e_i \tag{38}$$

where $\Delta\beta$ is the coefficient from the single-factor model. Our model theorises that $\Delta\beta$ shows the percent of variance that is in excess of fundamentals. If excess comovement results in increased variance, α_1 should be positive. The results are presented in Table 20.

Table 20: Second stage regression of increased variance on excess comovement

	α_0	α_1	R^2
1995–2018	-0.063807	0.51505***	0.0842
1995–2002	0.023131	0.27972	0.0247
2003–2008	-0.12761	0.57061*	0.0958
2009–2018	-0.1788	0.78087**	0.195

Note. This table presents the results of a second-stage regression to determine whether excess comovement results in increased variance. α_0 is the intercept. α_1 shows how much excess variance a 1% increase in excess comovement causes, for OBX inclusions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results are rather clear: a higher estimate for excess comovement results in a higher estimate for variance. This is a strong indication that the $\Delta\beta$ actually *does* pick up increase variance due to group-specific shocks.

The negative intercepts are somewhat puzzling, although none of them are anywhere near significant.

It is noteworthy that this test also shows an effect that increases over time, with both α_1 and the R^2 of the model increasing over time. The R^2 in the 2009–2018 period signalises that approximately 19.5% of the variation in inclusion stock's variance can be explained by the change in excess comovement. This is a high number considering the volatile nature of stocks, as well as their time varying volatility.

This finding that index inclusion leads to increased variance in excess of fundamentals may have profound implications for investments in Norway. It indicates that there is excess variance from being a member of the OBX index. This is an additional risk factor for OBX stocks, which is likely to be unpriced. This means that the excess comovement may cause OBX stocks to have a lower risk-adjusted return than they otherwise would have had.

8.4 Regression using the energy sector as an instrument for OBX shocks

The energy sector is the dominant sector in the OBX index. After 2003, the energy sector has been on average 45.11% of the OBX index. Figure 6 shows the precise breakdown over time.

This high share provides us with an opportunity to perform a robustness test, by examining whether the stocks joining the OBX comove more with the energy sector after inclusion. We run the regression:

$$R_{it} = \beta_0 + \beta_1 * R_{energy,t} + e_{it} \tag{39}$$

where $R_{energy,t}$ is the return of the Oslo Børs energy sector at time t.

The null hypothesis is that a stock becomes no more similar to energy stocks due to joining the OBX index. The alternative hypothesis is that there is excess comovement from joining the OBX index, and that since the energy sector dominates the OBX, this causes the stock to comove more with the energy sector.

We find that in the final period, $\Delta\beta_1$ is estimated to be 0.1284, significant at the 1% level (SE 0.0409). This means that in the final period, inclusions comove more with the energy sector after joining the OBX index. We consider the possibility that these results could be due to all stocks becoming more similar to the energy sector, and therefore also run the regression on the 11 samples from the matched samples section. None of them show a $\Delta\beta$ of either statistical nor economic significance.

The only explanation we can conceive as to why stocks added to the OBX index comove more with the energy index, is through excess comovement. This therefore strengthens the conclusion of our main test.

8.5 Evaluating the assumption of independence

In the main part of this thesis, we made a common assumption in comovement literature: that inclusions are independent of each other. This assumption does not necessarily hold, and in this section, we examine its validity.

There are many factors that affect all stocks on the index. Several stocks are added to the OBX index during each rebalancing – typically 2-5 – and for these, the regression has the same x-variable: R_{OBX}. Since exogenous shocks may affect all these inclusions in a similar manner, these stocks may see cross-sectional correlation, which would break the assumption of independence. Another danger to independence is that since the test is performed on every period, the post-period of one inclusion is the pre-period of another. This means that the shocks may also propagate between time periods, not just within one.

The most common way of controlling for cross-sectional dependence has been to follow the lead of the seminal paper within the field. Barberis et al. (2005) attempted to do so by estimating the standard errors through simulation. This has the implicit assumption that the net effect of the shocks on the delta beta is zero. That is not necessarily the case. We find this to be too simple a solution to the problem of independence, and we therefore create a model which allows us to analyse the extent to which the betas are independent. This also helps us analyse whether the other assumptions of our model may be broken.

We employ a multivariate maximum likelihood model which calculates the betas codependently. The log-likelihood iterates by attempting to find which parameters would be the most likely to create the observed distribution. We run the following regression

$$R_i = R_{OBX} * \beta_i + E_i \tag{40}$$

This is the same equation as in the single-factor model, but the calculation differs in a key way. The regression is now run as a multivariate general linear model, and allows for the β_i values to be cross-correlated. This means that we depart from the traditional finance definition of beta as the stock's covariance against the market over the variance of the stock, which we used in our model earlier. Instead, the beta is calculated as

$$\beta = \frac{R'_{OBX} * \Sigma_E^{-1} * R_i}{(R'_{OBX} * \Sigma_E^{-1} * R_{OBX})} \tag{41}$$

This is the standard setup for a multivariate general linear model (MathWorks, 2017). It fits very nicely with what we are trying to estimate. A few words on precisely what the model predicts.

The Σ_E is the inverted variance-covariance matrix of the errors terms E. The inverse of a variance-covariance matrix has the property that its elements represent the partial correlation between the variables (Barua, 2017; Trevor, Robert, & JH, 2009). The Σ_E therefore represents the extent to which the error terms of the different stocks are correlated, after controlling for all other variables.

Under the assumption that every stock is independent, Σ_E^{-1} becomes an identity matrix, since every stock is perfectly correlated with itself, and independent of every other. The equation then becomes $\beta = \frac{R'_{OBX} * I * R_i}{(R'_{OBX} * I * R_{OBX})}$. This equation is in expectancy equal to covariance over variance - the standard definition of beta in finance, under the assumption that the return of the stock and OBX are zero mean stocks. That is since $Cov(R_i, R_{OBX}) = E(R_i * R_{OBX}) + E(R_i) * E(R_{OBX})$, which if $E(R_i)$ or $E(_{ROBX}) = 0$, becomes simply $cov(R_i, R_{OBX}) = E(R_i * R_{OBX})$, and the same for variance.

So if stocks are truly independent, this model will calculate the traditional finance betas. But if they are not, the model will attempt to find the parameters that maximise the maximum likelihood function

$$\begin{aligned} logL(\beta, \Delta_E | R_i, R_{OBX}) &= \frac{1}{2} nd * log(2\pi) + \frac{1}{2} log(det(\Sigma_E)) \\ &+ \frac{1}{2} \sum_{i=1}^{n} (R_i - R_{OBX}\beta)' * \Sigma_E^{-1} * (R_i - R_{OBX}\beta) \end{aligned} \tag{42}$$

The driving force of this equation is the last term, which can be interpreted as the squared errors of the model controlling for partial correlations with the other errors. The optimal beta is then the beta that minimises the squared errors controlling for partial correlations with other errors. If the additions to the OBX are independent, this should precisely equal the betas found in the univariate regression of Section 4.1. If, however, the additions are cross-correlated, the betas from this multivariate test will not equal the betas of the univariate regression. Our null hypothesis is therefore that the univariate and multivariate betas are equal, while the alterative hypothesis is that they are not.

H0: $\Delta\beta_{Univariate} = \Delta\beta_{Multivariate}$

H1: $\Delta\beta_{Univariate} \neq \Delta\beta_{Multivariate}$

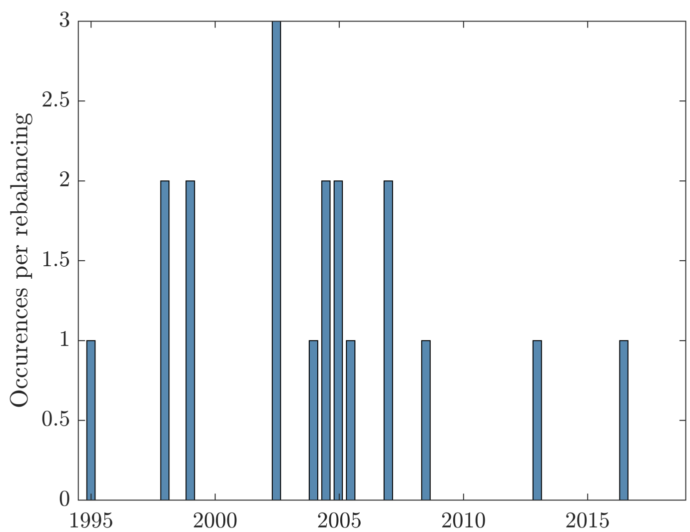
The results at the aggregate level are presented in Table 21. The results for 1995-2002 and 2009-2018 are for all intents and purposes equal in the univariate and the multivariate tests. But in the 2003-2008 period, they differ quite a bit. An examination

Table 21: Comparison of multivariate and single factor regressions

	$\Delta\beta_M$	SE($\Delta\beta_M$)	tStat$_M$	$\Delta\beta_U$	SE($\Delta\beta_U$)	tStat$_U$
1995–2018	0.05776	0.021768	2.6537	0.07203	0.024419	2.9497
1995–2002	0.014887	0.30376	0.4897	-0.011	0.03640	-0.0297
2003–2008	-0.00380	0.042265	-0.0898	0.02580	0.0460	0.5611
2009–2018	0.22164	0.044084	5.209	0.2191	0.0501	4.3714

Note. This table reports the summary statistic of the comparison of the multivariate and the single factor regressions for the different time periods. $\overline{\Delta\beta}$ is the average change in beta, SE is the standard error, and tStat is the variable test statistic. The subscripts M and U denotes the multivariate and univariate version of the single factor regression respectively.

Figure 16: Beta correlations over 0.2 per rebalancing



Note. This figure shows how many pairs of stocks have $\Delta\beta$ that have a correlation between them of over 0.2, per period.

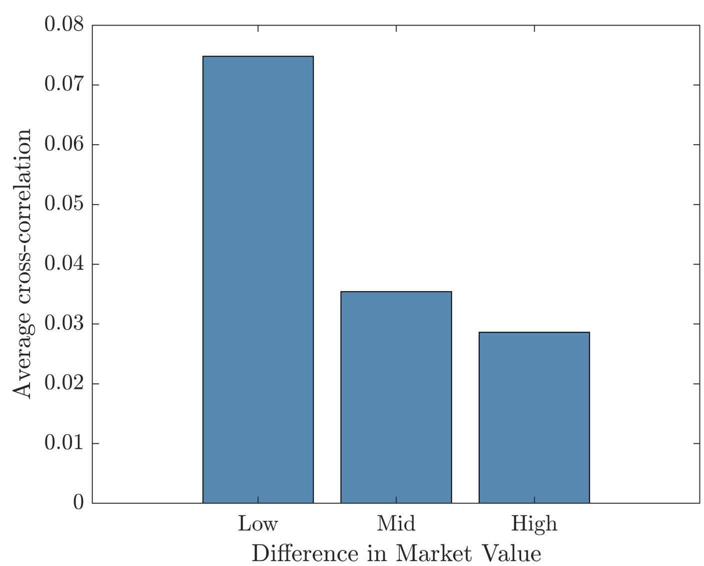
shows that this is because there is far more cross-correlation between the stocks in this period.

To evaluate the amount of cross-correlation, we use the coefficient variance-covariance matrix to look at the covariance between the $\Delta\beta$ estimates. We turn the variance-covariance matrix into the regression coefficient correlation matrix, and use $cov(\Delta\beta_i, \Delta\beta_j)$ as our estimate for the amount of cross-correlation between additions i and j. Figure 16 is a plot of every case where the correlation between two $\Delta\beta$ is larger than 0.2.

There are 18 pairs of additions which have a correlation of more than + 0.2. Of those, 12 are in the 2003-2009 period. There are a couple of interesting facts about these additions. Every pair of stocks which has high cross-correlation, comes from the same industry. With one exception, they all come from shipping, fishing or oil. These are all industries that primarily export, and which are subject to international prices. Changes in expectations about future prices are therefore likely to affect them all similarly. Exogenous shocks to international prices will in other words cause cross-correlation between stocks in all of these industries. It highlights the need to investigate whether there may be a systematic trend in which industries join, and whether this trend explains OBX returns. This was a large part of our motivation for controlling for industry in Section 5.

A second interesting fact is that the high-correlation pairs are all of similar size in terms of market capitalisation. Of the 18 pairs, 10 have a market cap ratio where the largest firm is less than twice the size of the smallest, and 15 have a ratio where the largest is within 3 times the size. This trend remains clear for the entire dataset – similarly sized firms have more cross-correlation, as Figure 17 shows.

Figure 17: Relation between difference in market capitalisation and cross-correlation in delta betas



Note. This figure shows the average cross-correlation of inclusions, dividing the inclusions into three buckets based on different in market capitalisation. For pairs in low, the largest firm is less than twice as large as the smallest. Pairs in mid have the largest between double and quadruple the size of the smallest. High has pairs where the largest is more than four times as large as the smallest.

We verify the relation between market value and cross-correlation with a regression, in the shape of $Corr(\Delta\beta_{ij}) = \eta_0 + \eta_1 log(\frac{MV_{Largest}}{MV_{Smallest}}) + e$. The regression yields a significant negative η_1.

It is clear that both industry membership and difference in market size affect the size of cross-correlation that additions experience – they are not independent of each other. But the effect of the cross-correlation is rather small in our dataset, and does not lead to large problems on the aggregate level. This is partly because the OBX index sees few additions per period (typically 2-5). For larger indexes that see far more additions at the same time, such as the S&P 500 index or the FTSE 100 index, cross-correlation is likely to be much higher. Our results indicate that it would be wise to perform a more thorough examination of cross-correlation than what has been done in those indexes.

9 Discussion

Before we conclude this thesis, we present a discussion on two of our most striking findings. Firstly, we address our finding that volume traded affects comovement in Norway, and consider why this may be the case. Secondly, we briefly discuss the growth in excess comovement.

9.1 Volume traded and liquidity

Our results indicate that there is a relation between increased volume traded and increased comovement with the indexes in Norway. In the analyses of this thesis, we considered changes in volume traded to be a variable that needed to be controlled for, in order to accurately estimate excess comovement. We did not focus much on *why* volume traded increases comovement with the Norwegian stock indexes, as that is not the main topic of this thesis. It is, however, an interesting phenomenon that is worth discussing.

One possibility is that volume traded works as a proxy for liquidity. We tested three other proxies for liquidity in Section 5.5 – the ILLIQ measure from Amihud (2002) measure, the relative bid-ask spread, and the liquidity measure of Næs et al. (2009). None of those had explanatory power on comovement for OBX inclusions. In the case of the Amihud ILLIQ measure, our findings in Section 8.3 indicate that the reason may be an endogeneity problem, and that the measure is misspecified for studying excess comovement.

Recall that the Amihud ILLIQ measure is calculated as:

$$ILLIQ_i = \frac{1}{n}\sum_{t=1}^{T}\frac{abs(R_{it})}{V_{it}} \tag{21}$$

As returns are approximately mean zero, the numerator is approximately the standard deviation of the stock. We have shown that index inclusion affects both the numerator and the denominator for inclusions. The measure therefore considers that the OBX inclusions have become no more liquid, in the period after inclusion than they were before. Other metrics indicate that the inclusions become more liquid: the stock is traded more, and has a smaller bid-ask spread. Næs et al. (2009) note that liquidity has three main dimensions: how much it costs to trade, how fast the stock can be traded, and how many shares it is possible to trade. By each of these, the stock is more liquid after inclusion, but the Amihud measure does not consider that to be the case, because it is affected by the increased variance.

For stocks that are not added to the OBX index, the change in the Amihud ILLIQ measure is a perfectly fine measure, as they are not subject to an exogenous shock which increases both volume traded and the volatility. This means that an inclusion and a non-inclusion with the same change in the Amihud measure, likely saw different increases in true liquidity. We therefore pose that it may be a misfit tool for measuring excess comovement.

Volume traded by itself, on the other hand, is not biased by the increased volatility from excess comovement, and is therefore unbiased as a comparison tool. It may therefore be a better estimate than the ILLIQ measure is for estimating liquidity in an excess comovement setting.

If volume traded works as a proxy for liquidity, why does liquidity affect comovement? A plausible explanation is the clientele effect from liquidity literature (Amihud, Mendelson, Pedersen, et al., 2006). Investors require compensation for trading costs. Short term investors depreciate their trading costs over a short period of time, and are therefore limited to buying assets with a low trading cost. Long term investors depreciate trading costs over a longer period of time, and therefore specialise in the assets that provide them with the highest return – assets with higher trading costs. The result is that stocks with low liquidity see a different clientele of investors than stocks with high liquidity.

If the investors of highly liquid stocks and illiquid stocks are different, then it appears likely that the investors of these groups experience different forms of shocks. As a stock increases in liquidity, its investors become more and more similar to the investors who own the most liquid stocks. In Norway, the OBX index which we measure against, *is* the most liquid stocks, and thus a stock seeing increasing liquidity should see more comovement with the index, due to having more correlating shocks.

This explanation for the relation between comovement and liquidity does in other words stem from the same source as the demand based view of comovement. Just as index membership causes a change in investor clientele, so does increased liquidity, and both of these cause increased comovement.

We have one finding which supports the idea that increased liquidity causes a change in clientele which causes increased comovement, and one finding which contradicts it.

The supporting finding is: liquidity causes increased comovement against the OBX, while momentum does not, but the opposite is the case on market capitalisation based indexes. On a market capitalisation based index, the investors owning the index are those with the largest preference for large stocks. Momentum stocks increase in size, and the investors therefore become more and more similar to those owning the index. Therefore, momentum causes increased comovement with market capitalisation based indexes. On a liquidity based index such as the OBX, the investors are those with a preference for highly liquid stocks, and so a stock increasing in price, but not liquidity, would not see increased comovement with the index. This is precisely what we observe, and is strong support for the clientele view.

The contradicting finding is that for the sample stocks, liquidity causes increased comovement also with the non-OBX index. The non-OBX index does not have investors with a preference for highly liquid stocks – if anything, its investors have a preference for illiquid stocks, as that is what the index consists of. The clientele view would therefore suggest that the stocks increasing in liquidity should see increased comovement with the OBX and reduced comovement with the non-OBX, but that is not what we observe. We observe similar increases in comovement with the OBX and non-OBX indexes. That is not possible to explain with the clientele view.

We do therefore not conclude on why increased volume traded causes increased comovement. There is no answer in existing comovement literature, as it has not examined volume traded. It is important for both Norwegian practitioners and academics to understand which factors drive the Norwegian stock market. We have in this thesis highlighted that excess comovement needs to be accounted for, but we were unable to conclude on the effects of volume traded. We leave that for future researchers, and believe it is a highly interesting topic for further study.

9.2 The time trend of excess comovement

Our findings indicate that there is excess comovement after controlling for changes in fundamentals. We have examined the potential effects of several fundamentals, but our tests are far from exhaustive: stock prices are affected by several factors. We have shown that index inclusion is not an information-free event, and that by controlling for volume traded, approximately a third of the initially found excess comovement vanishes. It is possible that there are other systematic traits for index inclusions to the OBX index, that we have not been able to detect. This is a limitation in our thesis.

One of the strongest arguments that there is excess comovement, is the time-trend. OBX inclusion rules have been unchanged since 1996. If there is something systematic about how stocks are added to the OBX index, and this is what causes the comovement, why did stocks joining the index only start comoving strongly after 2009?

This is hard to reconcile with the fundamental theories of comovement. There are many potential causes within the demand perspectives of comovement. One of these is strategies which involve buying or selling the whole index at once, cause excess comovement (Vijh, 1994; Barberis et al., 2005; Claessens & Yafeh, 2012). The OBX has recently seen an increase in the trade of index-linked investments, such as Exchange Traded Funds (ETFs) and futures, and this is therefore a plausible cause of the excess comovement. Identifying this is outside the scope of this thesis. We present some statistics on the growth of OBX futures and ETFs in Appendix E, but leave it to future researchers to examine this thoroughly.

10 Conclusion

The topic of this thesis is one of the most fundamental aspects of asset pricing: the comovement of stock prices. Our primary focus has been on establishing the degree to which there is comovement in the Norwegian stock market that cannot be explained by fundamental factors.

We have presented several tests to determine whether there is excess comovement in the Norwegian stock market. The first of these is the standard test for comovement, a market-model regression using index inclusion as a natural experiment. This regression finds substantial comovement, particularly from 2009 to 2018. The comovement is of similar magnitude to that which has previously been found by studying comovement in countries which base index inclusion on market capitalisation.

Critics have claimed that the comovement in indexes which base inclusion on market capitalisation, is due to index inclusion not being an information-free event. We create a model which clearly defines all the assumptions necessary for the standard comovement test to accurately identify excess comovement. We have tested whether each of these assumptions hold. We test both variables which previous critics have suggested break the assumptions, and several new factors. None of the previously identified factors can explain the excess comovement in Norway. However, we reveal that a previously unidentified variable does cause comovement in Norway: the volume traded. Volume traded causes all stocks in Norway to see increased comovement with the OBX index, and since inclusions tend to see increased volume traded, the standard comovement test over-estimates the comovement effect of index inclusion.

To identify how large the excess comovement from index membership is after controlling for volume traded, we perform two tests. A matched sample approach, and a regression discontinuity design. Both yield the same result: there is excess comovement in the Norwegian stock market. This is a discovery that has not been made before, and that has profound implications for investments in Norway. In the period of 2009-

2018, we estimate that excess comovement is equal to 14% of the variance of the OBX index.

The findings in this thesis highlight the need for careful use of the standard comovement test. Previous literature has highlighted that momentum causes comovement on indexes which base inclusion on market capitalisation. We find that the assumptions of the model are broken also on an index which bases inclusion on volume traded, but that it is not broken by the same variables. Which metric the index bases inclusion on, appears to determine how the assumptions are broken. Researchers must strive to identify and control for variables which may break the assumptions necessary for the model to provide accurate results.

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Appendices

A Excluding the inclusion from the OBX index

There is a mechanical challenge in running inclusion-based comovement tests, such as for instance the single-factor model.

$$R_{it} = \alpha_i + \beta_i R_{OBX,t} + \epsilon_{it} \tag{A1}$$

After inclusion, the stock is part of the OBX index. The left hand variable is therefore part of the right-hand variable. As the inclusion comoves perfectly with itself, this may cause us to overestimate the beta. This is not a problem on indexes such as the S&P 500, where the 500th largest stock makes up a extremely small part of the whole index. But it may be a problem on the OBX index, where there are just 25 stocks. The median weight in the OBX index of the inclusions we use in our regressions is 0.76% (the median is 1.51%, driven up by for instance Statoil having a weight of 27.3% when it joined), so it would not cause a large over-estimation, but it would cause a small one.

When we regress stock i on the OBX index, we therefore subtract stock i from the OBX index. We then scale this OBX-minus-stock-i index up by dividing by $1 - W_{it}$, so that the OBX without stock i has the same total weight as the actual OBX index. Our calculation is formally as follows:

$$R_{OBX,it} = \frac{R_{OBX,t} - W_{it} * R_{it}}{1 - W_{it}} \tag{A2}$$

where $R_{OBX,it}$ is the OBX excluding stock i. $R_{OBX,t}$ is the actual OBX index at time t (including stock i), W_{it} is the weight of stock i in the OBX index, and R_{it} is the return of stock i at time t. $R_{OBX,it}$ is then the X-variable we use whenever we regress on stock i.

Since OBX inclusions tend to be small (with a median weight of 0.76%), this does not majorly impact our findings, but we would have overestimated slightly had we not performed this correction. For instance, in the single-factor model, we estimate that the overall beta is 0.07203. Had we instead run the regression without excluding the inclusion from the OBX, we would have found an estimate of 0.084676

B The assumption of unchanged OBX variance

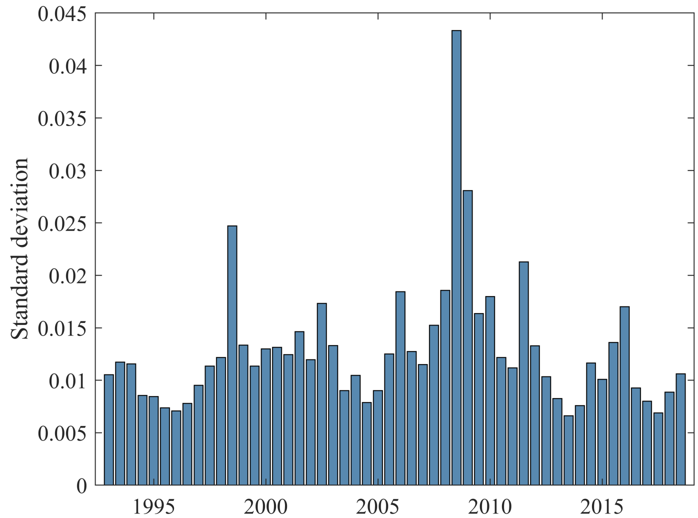
In the single-factor model, we made the assumption that the variance of the OBX is the same in expectancy over time. Put differently, that OBX variance can be considered a stochastic variable which is drawn from the same distribution every time. The whole idea behind studying index inclusion is that index inclusion is supposed to be an information-free event. The change in beta then picks up the increase is comovement. The beta itself is calculated as the inclusion's covariance with the market, divided by the market variance. If the market variance changes in a systematic fashion, this may then bias the results. In this section, we evaluate whether changes in OBX variance may be a problem for the validity of the test.

Figure B1 shows the development of OBX volatility over time. There is no time-trend for the full period, which is a sign that the assumption that variance is drawn from the same distribution holds. There are, however, trends within each *sub-period*. Variance rose consistently within the first sub-period of 1995 through 2002. The second period of 2003 through 2008 saw the spike of the financial crisis. The final period from 2009 to 2018 saw a general trend of decreasing variance from the high levels in 2009, especially in the first part. Changes in volatility could therefore potentially be a problem for the test.

It is important to note that changes in variance are only a problem if there is not an equal and corresponding increase in the covariance of the stock. This is intuitively likely, as the variance of the index is the value-weighted sum of all the variances of its constituents.

We run a second-stage regression to determine whether changes in OBX variance affect the estimates of change in comovement. This second-stage regression is $\Delta\beta_i = \alpha_0 + \alpha_1 * \Delta\sigma_{OBX} + e_t$, where $\Delta\beta$ is the change in beta of the inclusions from before to after inclusion, and $\Delta\sigma_{OBX}$ is the change in OBX variance in the same period. This regression yields a non-significant return (p-value of 0.56) and a negative adjusted R^2. This signals that changes in OBX variance do not bias the estimates of $\Delta\beta$.

Figure B1: Volatility of the OBX index for each rebalancing period



Note. This graph shows the standard deviation of returns within each rebalancing period of the OBX. Each rebalancing period is approximately 6 months.

C Bid-ask spread as an estimator of comovement

The following table displays the regression output of the second-stage regression between the bid-ask spread and excess comovement. ζ_1 is not significant for any period, and the R^2 is low, so we conclude that the bid-ask spread does not explain much about excess comovement on the OBX.

$$\Delta\beta_i = \zeta_0 + \zeta_1 * \Delta BidAskSpread_i + e_t \tag{C1}$$

Table C1: Regression of change in the LIQ measure on comovement

	ζ_0	ζ_1	R^2
1995–2018	0.077606**	0.045	0.00318
1995–2002	0.018254	0.016001	0.000428
2003–2008	0.05638	0.11304	0.0152
2009–2018	0.21581**	0.020627	0.00122

Note. This table shows the coefficients of the change in bid-ask spread on the change in beta. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

D Derivation of the two-factor model

In this section, we derive a model that performs a similar test as our main model, but tests for the combined effects of OBX shocks and non-OBX shocks. This model allows changes in fundamentals. We do this by running a two-factor regression, where we regress the return of the stock on both the return on the OBX index, and the non-OBX index. The two-factor regression we run is the following:

$$R_{it} = \alpha_i + \beta_{1i} R_{OBX,t} + \beta_{2i} R_{Non,t} + e_{it} \tag{D1}$$

where β_1 is the loading against the OBX index, while β_2 is the loading against the non-OBX index.

D.1 Beta-one

In expectancy, the $\beta 1$ coefficient is equal to:

$$\beta_{1i} = \frac{cov(R_{it}, R_{OBX,t}) * var(R_{Non,t}) - cov(R_{it}, R_{Non,t}) * cov(R_{OBX,t}, R_{Non,t})}{var(R_{OBX,t}) * var(R_{Non,t}) - cov(R_{OBX,t}, R_{Non,t})^2} \tag{D2}$$

For the same reasons as in the original model in Section 4.2, we assume that the expected variance of the OBX index and non-OBX index are unchanged over time, and that the same is the case for the covariance between the OBX index and the non-OBX index. For easier reading, we redefine the variance of the indexes as VX for the OBX and VN for the non-OBX index, and VXN for the covariance between OBX and Non. The equation is then

$$\beta_{1i} = \frac{cov(R_{it}, R_{OBX,t}) * VN - cov(R_{it}, R_{Non,t}) * VXN}{VX * VN - VXN^2} \tag{D3}$$

Recall that in our model in Section 4.2, we derived that the covariance between stock i and the OBX index prior to inclusion is

$$cov(R_i^b, R_{OBX}^b) = \sum_{j=1}^{n} \sum_{k=1}^{n} \lambda_{ij}^b \lambda_{OBXk}^b C_{jk}^b \tag{D4}$$

where λ_{ij} is stock i's loading on fundamental j, $\lambda_{OBX,k}$ is the OBX index' loading on fundamental k, and C is the variance-covariance matrix of fundamentals.

After rebalancing, OBX inclusions become victim to the exogenous shocks to the OBX index, and their covariance becomes

$$cov(R_i^a, R_{OBX}^a) = \sum_{j=1}^{n}\sum_{k=1}^{n} \lambda_{ij}^a \lambda_{OBXk}^a C_{jk}^a + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2 \tag{D5}$$

where $\sigma_{S_{OBX}}^2$ is the variance of the exogenous shocks to the OBX index, and γ_i^{OBX} is stock i's exposure to those shocks.

Moving on to the covariance with the non-OBX index. Before inclusion, the stock is exposed to the shocks to the non-OBX index.

$$cov(R_i^b, R_{NON}^b) = \sum_{j=1}^{n}\sum_{k=1}^{n} \lambda_{ij}^b \lambda_{Non,k}^b C_{jk} + \gamma_i^{b,NON} * \sigma_{S_{NON}}^2 \tag{D6}$$

If we insert these into the estimate of β_{1i}, then that becomes the following prior to inclusion:

$$\beta_{1i}^b = \frac{\sum_{j=1}^n \sum_{k=1}^n \lambda_{ij}^b \lambda_{OBXk}^b C_{jk}^b * VN - (\sum_{j=1}^n \sum_{k=1}^n \lambda_{ij}^b \lambda_{Non,k}^b C_{jk}^b + \gamma_i^{b,NON} * \sigma_{S_{NON}}^2) * VXN}{VX * VN - VXN^2} \tag{D7}$$

We can simplify this to

$$\beta_{1i}^b = \frac{\sum_{j=1}^n \sum_{k=1}^n \lambda_{ij}^b C_{jk}^b * (\lambda_{OBXk}^b * VN - \lambda_{Non,k}^b * VXN) - \gamma_i^{b,NON} * \sigma_{S_{NON}}^2 * VXN}{VX * VN - VXN^2} \tag{D8}$$

The stocks that are included on the OBX index become victim to the exogenous shocks affecting OBX shocks, but are no longer affected by exogenous shocks to non-OBX stocks. Their beta after inclusion is then

$$\beta_{1iInc}^a = \frac{\sum_{j=1}^n \sum_{k=1}^n (\lambda_{ij}^a \lambda_{OBXk}^a C_{jk}^a + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2) * VN - (\sum_{j=1}^n \sum_{k=1}^n \lambda_{ij}^a \lambda_{Non,k}^a C_{jk}^a) * VXN}{VX * VN - VXN^2} \tag{D9}$$

This simplifies to

$$\beta_{1iInc}^a = \frac{\sum_{j=1}^n \sum_{k=1}^n \lambda_{ij}^a C_{jk}^a * (\lambda_{OBXk}^a * VN - \lambda_{Non,k}^a * VXN) + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2 * VN}{VX * VN - VXN^2} \tag{D10}$$

Under the same assumptions as in the original model (fundamentals are unchanged, loading on fundamentals unchanged), the $\Delta\beta_{1iInc}$ is then

$$\Delta\beta_{1iInc} = \frac{\gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2 * VN + \gamma_i^{b,NON} \sigma_{S_{NON}}^2 * VXN}{VX * VN - VXN^2} \tag{D11}$$

This $\Delta\beta_{1iInc}$ is then a measure of the total covariance due to *both* seeing increased exposure to S_{OBX} and decreased exposure to S_{NON}.

D.2 Beta-two

We calculate $\Delta\beta_{2iInc}$ in a similar way as $\Delta\beta_{1iInc}$. Just as $\Delta\beta_{1iInc}$, this expression is a measure of the combined effects of OBX and Non-OBX shocks. While those shocks will both drive $\Delta\beta_{1iInc}$ in a positive direction, they push $\Delta\beta_{2iInc}$ in a negative direction. The calculations can be shown as following:

In expectancy, the β_2 coefficient is equal to

$$\beta_{2i} = \frac{cov(R_{it}, R_{Non,t}) * var(R_{OBX,t}) - cov(R_{it}, R_{OBX,t}) * cov(R_{Non,t}, R_{OBX,t})}{var(R_{Non,t}) * var(R_{OBX,t}) - cov(R_{Non,t}, R_{OBX,t})^2} \tag{D12}$$

As for β_{1i} in Appendix D, we here assume that the expected variance of the OBX index and non-OBX index, and that the covariance between the OBX index and the non-OBX index are unchanged over time. We do also here redefine the variance of the indexes as VX for the OBX and VN for the non-OBX index, and VXN for the covariance between OBX and Non. This gives:

$$\beta_{2i} = \frac{cov(R_{it}, R_{Non,t}) * VX - cov(R_{it}, R_{OBX,t}) * VXN}{VN * VX - VXN^2} \tag{D13}$$

We use from Section 4.2, were we derived that the covariance between stock i and the Non-OBX index is prior to inclusion be equal to:

$$cov(R_i^b, R_{NON}^b) = \sum_{j=1}^{n}\sum_{k=1}^{n} \lambda_{ij}^b \lambda_{Non,k}^b C_{jk} + \gamma_i^{b,NON} * \sigma_{S_{NON}}^2 \tag{D14}$$

Meaning that before inclusion, the stock is exposed to the shocks to the non-OBX index.

After rebalancing, OBX inclusions become victim to the exogenous shocks to the OBX index, and their covariance becomes:

$$cov(R_i^a, R_{OBX}^a) = \sum_{j=1}^{n}\sum_{k=1}^{n} \lambda_{ij}^a \lambda_{OBXk}^a C_{jk}^a + \gamma_i^{a,OBX} * \sigma_{S_{OBX}}^2 \tag{D15}$$

We then obtain our estimates for β_{2i} prior to and following inclusion. By inserting the covariance terms we get:

$$\beta_{2i}^{b} = \frac{(\sum_{j=1}^{n}\sum_{k=1}^{n}\lambda_{ij}^{b}\lambda_{Nonk}^{b}C_{jk}^{b}+\gamma_{i}^{b,Non}*\sigma_{S_{Non}}^{2})*VX-(\sum_{j=1}^{n}\sum_{k=1}^{n}\lambda_{ij}^{b}\lambda_{OBXk}^{b}C_{jk}^{b})*VXN}{VX*VN-VXN^{2}} \tag{D16}$$

$$\beta_{2i}^{a} = \frac{(\sum_{j=1}^{n}\sum_{k=1}^{n}\lambda_{ij}^{a}\lambda_{Nonk}^{a}C_{jk}^{a})*VX-(\sum_{j=1}^{n}\sum_{k=1}^{n}\lambda_{ij}^{a}\lambda_{OBXk}^{a}C_{jk}^{a}+\gamma_{i}^{a,OBX}*\sigma_{S_{OBX}}^{2})*VXN}{VX*VN-VXN^{2}} \tag{D17}$$

Which equals:

$$\beta_{2i}^{b} = \frac{\sum_{j=1}^{n}\sum_{k=1}^{n}\lambda_{ij}^{b}C_{jk}^{b}*(\lambda_{Nonk}^{b}*VX-\lambda_{OBX,k}^{b}*VXN)+\gamma_{i}^{b,NON}*\sigma_{S_{NON}}^{2}*VX}{VX*VN-VXN^{2}} \tag{D18}$$

$$\beta_{2i}^{a} = \frac{\sum_{j=1}^{n}\sum_{k=1}^{n}\lambda_{ij}^{b}C_{jk}^{b}*(\lambda_{Non,k}^{a}*VX-\lambda_{OBX,k}^{a}*VXN)-\gamma_{i}^{a,OBX}*\sigma_{S_{OBX}}^{2}*VXN}{VX*VN-VXN^{2}} \tag{D19}$$

Under the same assumptions as in the original model (fundamentals are unchanged and loading on fundamentals unchanged), the $\Delta\beta_{2iInc}$ is then:

$$\Delta\beta_{2iInc} = \frac{-(\gamma_{i}^{a,OBX} * \sigma_{S_{OBX}}^{2} * VXN + \gamma_{i}^{b,Non}\sigma_{S_{NON}}^{2} * VX)}{VX * VN - VXN^{2}} \tag{D20}$$

E Index construction and investment strategies

A topic we briefly touch in this thesis, but which is outside its main scope, is how index construction may affect which investment strategies are profitable in a country. We present some interesting pieces of information, that we believe are worthwhile to study, but leave it to future researchers to perform a thorough analysis.

In this thesis, we documented that momentum does not substantially impact comovement in Norway, even though it has been found to do so in other countries. It has previously been found that momentum has relatively weak explanatory power of returns in Norway. One such finding is from Næs et al. (2009), who find that the investment strategy of buying the stocks with the highest momentum in Norway, and selling those with the lowest momentum, does not create excess returns in Norway between 1980 and 2006. Rouwenhorst (1998) had previously found that this investment strategy created excess returns in 11 of 12 different European markets up to 1995.[E1] The only country in which the momentum investment strategy did not work, was Sweden. Like Norway, Sweden's OMX 30 index bases inclusion on the volume traded (Nasdaq, 2019). This means that while momentum investment strategies have been found to work in most countries, they do not provide excess returns in Norway and Sweden, where the OBX and OMX30 base membership on volume traded. This is an indication that how the indexes in a country base inclusion, affects which investment strategies work in that country. We consider this to be a topic that may be interesting topic for further study.

F Preliminary statistics on effects of index-linked investments

Estimating the effects of index-linked investments on comovement in Norway is a highly interesting topic for further research. This appendix presents a simple overview of the developments in futures trading and ETFs on the OBX index.

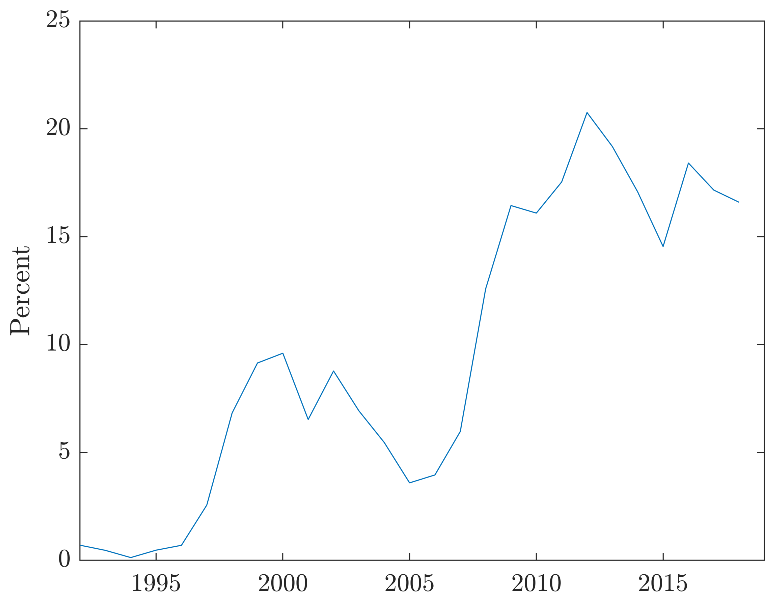
[E1] Rouwenhorst (1998) found excess returns using a momentum strategy in Norway for 1980 to 1995, but Næs et al. (2009) do not find excess returns for the full period of 1980 to 2006

Strategies that involve buying or selling the whole index at once are an important part of the demand-based view of comovement (Vijh, 1994; Barberis et al., 2005). The OBX is a tradable index, and there is a large amount of derivatives trade on the index. This includes futures, options, ETFs, and ETNs, that are linked to the OBX index.

As mentioned in Section 3, OBX futures were in 2018 the most traded product on Oslo Børs, with a market value of volume traded of 216 billion kroner. That is equal to approximately 16% of the market value of all equity trade on Oslo Børs. The trade of OBX futures has risen over time. In 2006, OBX futures trade was equal to only 3.96% of the total trade of equities on Oslo Børs, but this grew to 20.75% in 2012.

This figure displays the development of OBX futures trade a percentage of the total trade of shares on the OBX index. It illustrates that there is a growing trend in futures trading with the OBX as the underlying.[F1]

Figure F1: OBX future trade as percent of the total trade of shares



Note. This graph shows how large the value of trades of OBX futures is as compared to the total trade of equities on Oslo Børs. It is calculated as the market value of OBX futures trade, divided by the sum of all trades of equities on the Oslo Børs.

ETFs with the OBX index as the underlying were introduced in 2005 (Gjerde & Sættem, 2014), and have grown strongly in popularity. In 2018, data from Oslo Børs

[F1] Authors' calculations based on data from Oslo Børs.

shows that the value of trades of ETFs with the OBX as the underlying, was approximately 20.9 billion kroner in 2018.

There are therefore signs that the growth in both derivatives trade and ETFs happened slightly before the growth in excess comovement presented in this thesis. We have not identified a causal relation between these, as that is outside the scope of this thesis. Investigating that connection is a potentially interesting topic for further research.