EXCESS COMOVEMENT BY INDEX EVENTS

AN EXTENSION TO THE SWEDISH STOCK MARKET

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Abstract:

Using momentum and fundamental changes as control variables for stocks subject to index events have shown to disprove previous evidence of excess comovement (Chen et al, 2016, Kasch and Sarkar, 2014, Von Drathen, 2014). This thesis examines if the control variables disprove excess comovement, to the same extent, when examining an index on another stock market outside the U.S. By replicating methods developed by Chen et al (2016), we show that for index additions to and removals from the Swedish index OMX Stockholm Benchmark, there is no support for the excess comovement hypothesis. With two univariate regressions and a matched sample approach controlling for momentum and size, previously found evidence of excess comovement can instead be explained by changes of the event stocks' fundamental betas. Further, we highlight differences in results that we argue stems from differences in index qualification processes and market microstructures. Despite these differences, we find no support of excess comovement caused by index events on the Swedish stock market.

Keywords:

Excess comovement, index effect, momentum, matching stocks, OMXSB

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1. Introduction

A way to challenge the traditional financial theory that asset pricing is solely explained by expected cash flows and discount rates (Fama, 1970), is to look at information free events that should not change these factors (Denis et al, 2003). One of such so called non-fundamental events are index changes where stocks are introduced to or removed from an index. From the traditional view, these are solely classification changes on the marketplace and theoretically separable from the fundamental asset value (Barberis et al, 2005). As index events also have the characteristic of being easily identifiable, they are a common tool to challenge the traditional theory of a frictionless market in the literature where focus has been on identifying excess return (Chen et al, 2016). Findings of excess returns can further be divided into two different methods, cumulative abnormal return (CAR) and excess comovement.

In the late 80's several important findings of CAR were presented by for example Schleifer (1986) who presented downwards sloping demand curves and Harris and Gurel (1986) that presented the price pressure hypothesis. Another wave of findings came in the early 00's with expansions of earlier research and more theories of why abnormal returns were found. These include, Chen et al (2004) who presented the investor awareness hypothesis, Denis et al (2003) that suggest that inclusions are not information free and Wurgler and Zhuravskaya (2002) that presented the imperfect substitutes hypothesis.

Evidence of excess comovement was first presented by Vijh (1994) who presented two views; the traditional or frictionless-based view where comovement is explained by changes in an asset's fundamental factors and the friction- or sentiment-based view where excess comovement is explained by factors delinked to a stock's fundamentals. Vijh (1994) show evidence of the latter. The friction- or sentiment-based view was further divided into three theories; habitat, category and information diffusion. One classical study of comovement (Chen et al, 2016), was later presented by Barberis et al (2005) where they extend the research of Vijh (1994) and show evidence of excess comovement, especially in support of the habitat and category hypothesis.

In later years, two studies have presented results disproving non-fundamental excess return for each of the two methods respectively. Kasch and Sarkar (2014) present findings that increases in CAR are related to changes in fundamental performance and not to the inclusion itself, in part by using theories of momentum as a control variable. Chen et al (2016) does the same for excess comovement when they revisit the study of Barberis et al (2005). By adding another univariate regression and controlling for momentum, they do not find any support for the excess comovement hypothesis.

To further contribute to the subject, this paper examines the effect of index events on another index than the thoroughly investigated S&P 500, namely the Stockholm Exchange's OMX Stockholm Benchmark index. The indices differ in two important characteristics, where the first is qualification process (Denis et al, 2003) and the second is the microstructure of the market (Chen et al, 2016).

By conducting an empirical analysis similar to that of Chen et al (2016), we find no support of the excess comovement hypothesis on the Swedish market. Effects of the two mentioned differences can be seen in the results, yet these do not affect the lack of support found for the excess comovement hypothesis when controlling for momentum. Our results for the sample of stocks removed from the index are weaker than those found in previous studies (Barberis et al, 2005 and Chen et al, 2016), which we argue is a result of the mechanical disqualification process of the OMXSB. Furthermore, we show that the effects from a leads and lags adjustment (Dimson, 1979), are due to the microstructure of the market instead of information diffusion claimed by Barberis et al (2005). Also, we find that there is no effect on excess comovement caused by pre-trading which is possible on an index like OMXSB with a mechanical qualification process.

The rest of the paper is structured as follows: Section 2 provides a literature review of the studies most influential to this paper: Comovement (Barberis et al, 2005) and Comovement revisited (Chen et al, 2016), Section 3 covers the academic background and definitions of subjects relating to comovement and methods used in this paper, Section 4 shows a theoretical model based on Chen et al (2016) to evaluate and predict results in our empirical analysis, Section 5 covers the empirical method used, Section 6 presents our empirical results with adjacent analysis and Section 7 presents our conclusions.

2. Literature review

2.1 Comovement

The study conducted by Barberis et al (2005) extend the work of Vijh (1994). By looking at S&P 500 events they aim to distinguish between the traditional and friction- and sentiment-based views of return comovement. The authors add the application of a bivariate regression in addition to the univariate used by Vijh (1994) which accounts for the return of non-S&P stocks and apply their method on more and newer data. The friction- and sentiment-based view suggest that in a bivariate regression the S&P 500 index beta should increase after inclusion while non-S&P(rest of the market) beta should decrease, and vice versa for a removal, and that changes should be stronger in more recent data.

The univariate regressions used, similar to those in Vijh (1994) analysis, present results that show larger changes in betas for the more recent data used, confirming their initial hypothesis. The results generated by the bivariate analysis also confirms the suggestions above, showing considerably larger increases in betas than the univariate, stronger effects for later subperiods and that the opposite pattern exists for removals. Barberis et al (2005) further attempted to distinguish the contribution from the three friction- and sentiment-based views, namely category, habitat and information diffusion, and found that for the daily bivariate regressions, information diffusion is accountable for up to two thirds of the effects.

2.2 Comovement revisited

The study revisits the work of Barberis et al (2005) after two working papers by Von Drathen (2014) and Kasch and Sarkar (2014) had challenged earlier proofs of CAR with fundamental changes and theories of momentum as control variables. As an example, they claim that stocks are being added to an index by performing fundamentally well before inclusion and not by an opposite causality. Chen et al (2016) therefore revisit two prior well known studies that support excess comovement, one for index changes (Barberis et al, 2005) and for stock splits (Green and Hwang, 2009) and add momentum as a control variable.

For the revisit on Barberis et al (2005), Chen et al (2016) add a univariate regression towards the group that the event stock are leaving which is new to the literature, they problematize the economic significance of the bivariate regression of Barberis et al (2015) and they conduct a matched sample approach based on momentum and size. Results from the added univariate regression show that event stocks do not only increase the loading of beta towards their new group but also to their old group, indicating an increased fundamental comovement towards all stocks. Tests of the model's parameter stability show that the economic significance of the bivariate regression used by Barberis et al (2005) is hard to quantify when other parameters than excess comovement are changing, limiting insights provided by this regression. Finally, the matched sample approach based on momentum find no support of the excess comovement hypothesis when comparing their two samples.

3. Academic background and definitions

3.1 The efficient market hypothesis

The hypothesis was first introduced by Fama (1970) who stated that the primary role of the capital market is allocation of ownership of the economy's capital stock. The allocation of ownership should further be driven by market prices that reflect all publicly available information. A market where all securities reflect all information through their prices would be seen as an efficient market.

3.2 Comovement

In a perfect capital market, comovement of stock prices with each other should correspond to the common variation in news of their fundamental value (working paper, Von Drathen, 2014). As Vijh (1994) however states, there are two views of comovement; the traditional- or fundamental-based view explained above and the friction- or sentiment-based view. The latter view find excess comovement in prices above the common comovement due to reasons that are unlinked to fundamentals.

For index changes, evidence for the friction-based view was first presented by Vijh (1994) and there has been growing evidence to support this view in other empirical research (Chen et al, 2016). This, in addition to index changes, includes sources such as;

stock-splits (Green and Hwang, 2009), stocks correlated with retail investors (Kumar and Lee, 2006) and stock's geographical headquarters (Pirinsky and Wang, 2006), to name some examples. In general, the most accepted explanation of the source to excess comovement is an asset class effect (Chen et al, 2016).

For index changes, the most recent studies are those reviewed in section 2, Barberis et al (2005) and Chen et al (2016). The first tries to distinguish effects between the three theories that give rise to asset classes and the friction- or sentiment-based view, as such, they are further described below.

3.2.1 Habitat theory

Investors tend to have preferred habitats when they allocate their funds, only investing in certain securities (Barberis et al, 2005). These habitats are partly affected by transaction costs, international trade restriction and lack of information. These habitats form subgroups of investors that allocate their funds in a similar way. As these subgroups of investors change their need of liquidity, risk aversion and sentiment they change their exposure to the assets in their habitat which implies that the returns of those assets have a common factor (Barberis et al, 2005). The theory hence suggest that the return of securities traded by a certain subgroup of investors comove.

3.2.2 Category theory

The second theory, analyzed by Barberis and Shleifer (2003), implies that investors tend to categorize certain securities into different subgroups, such as small-cap companies, large-cap companies and index companies. Investors then decide how to invest their funds based on which category the security belongs to, not looking at the individual asset level. If some of these investors are noise traders with correlated sentiment, and if they invest a sufficient amount to affect the price of the security, as they re-allocate their funds from one category to another the assets that are placed in the same category tend to comove, notwithstanding uncorrelated fundamental values (Barberis et al, 2005).

3.2.3 Information diffusion theory

The third view implies that different securities integrate information into their prices at different paces, due to some market friction (Barberis et al, 2005), such as lack of liquidity of the securities stock (Hou and Moskowitz, 2005). This view holds that assets with similar information incorporation pace have a common factor in their returns (Barberis et al, 2005). When good news about fundamental value is released, some stocks integrate it in their price immediately and move up together, while some stocks does it after some delay.

3.3 Non-synchronous trading

A possible problem when using data samples is that multiple time-series can be gathered simultaneously even if the underlying process for the data collected is not synchronous. An example of this is when collecting closing prices from a stock exchange. Even if all prices are collected simultaneously at closing, all of them need not to have been updated at this time, mostly as a result of the stock's trading volume. This induces autocorrelation into the time-series since a portion of the sample's prices from the previous day needs updating the following day (Lo and MacKinley, 1990).

Even if non-synchronous trading is seen as the most recognized source of autocorrelation in samples of daily stock prices, the amount of its effect and other sources of autocorrelation, such as market microstructures, are still under discussion in the literature (Kadlec and Patterson, 1999). The working paper of Säfvenblad (1997) illustrates that the sources of autocorrelation also could depend on the market studied. More specifically, he finds that autocorrelation on the Swedish Stock market is most likely due to a combination of non-synchronous trading and the investor behavior of profit-taking. The latter is a form of feedback trading where investors tend to realize profits to a greater extent than losses which consequently has an effect on the autocorrelation of the marketplace (working paper, Säfvenblad, 1997).

A way to more accurately estimate betas with autocorrelated time-series is presented by Dimson (1979). By adding leads and lags to a regression that estimates a stock's beta, Dimson (1979) show that the estimation better corresponds to the beta expected by theoretical models. Both Barberis et al (2005) and Chen et al (2016) use the Dimson adjustment in their methods. While Barberis et al (2005) claim that the adjustment identifies the effect of information diffusion, Chen et al (2016) find non-synchronous trading or microstructure effects as equally plausible.

3.4 Momentum

Stocks that have experienced high returns the past 3 to 12 months tend to outperform stocks that haven't during the preceding 12 months (Jegadeesh and Titman, 2001). Previous studies such as Barberis et al (1998), Daniel et al (1998) and Hong and Stein (1999) have attributed this to the inherent biases in the way investors interpret information, while Conrad and Kaul (1998) deem the profits gained by momentum strategies is due to cross-sectional variation in expected return, implying that momentum strategies are profitable even when the expected return doesn't change over time.

To control for the momentum effect on a stocks loading on beta, Chen et al (2016) apply a similar method as Jegadeesh and Titman (2001) and find that betas for winner stocks (stocks classified in the top decile) experience a statistically significant increase in beta of 0,295 over two years around portfolio formation. The same number for losing stocks (classified as the bottom decile) has a decrease of beta of -0,063. Furthermore, the middle deciles (3-7) betas did not experience a statistically significant change.

3.5 Index methodologies

3.5.1 S&P 500

The S&P 500's objective is to follow the large-cap segment of the U.S. equity market and to been seen as a proxy for the market as a whole. The selection of constituents of the S&P 500 is at the discretion of the Index Committee based on their eligibility criteria such as domicile, free float and market capitalization. Revision of constituents on the index is made quarterly by the committee (S&P Dow Jones Indices, 2020). The discretion of the committee has led to discussions if an inclusion or exclusion from the S&P 500 is in fact information free, even if that is what S&P Dow Jones Indices themselves claim (Denis et al, 2003).

3.5.2 OMX Stockholm Benchmark

The OMX Stockholm Benchmark index consist of the 90 or so largest companies in terms of turnover on the Stockholm Stock Exchange. In essence, all shares listed on the stock exchange are legitimate to be included in the index. However, some criteria have to be fulfilled, such as liquidity of the stock, industry target, free float and market capitalization limit. The goals of the criteria are to improve the index's investability by having a sufficient free float and a fair weighting. NASDAQ revise the index semi-annually, implementing the changes on the first trading day in June and December (NASDAQ, 2018). Unlike S&P 500, NASDAQ's selection process of the OMXSB index is mechanical.

4. Theoretical model

To be able to understand the economic significance and to predict the results of the empirical results in this study, a basic theoretical model will be set up, as previously has been done in the studies by Barberis et al (2005) and Chen et al (2016). As the later of the mentioned studies has based their model on the first, ours will directly be based on the model of Chen et al (2016) and indirectly on the one by Barberis et al (2005). As both previous studies describe, the model is not made to perfectly describe reality but rather to provide ability to predict results and a more comprehensible understanding of them. Through the model, an understanding of the features of the regressions that will be used later in the empirical analysis, and how they capture insights about the hypothesis of excess comovement can be established. Note that our model is the same to that of Chen et al (2016), with the exception that we do not use a bivariate regression and that explanations might differ.

4.1 Set up and assumptions

Assume that y_t is the return of a stock that changes its membership between group 1 and group 2 that has the returns x_{1t} and x_{2t}. This event is comparable to a stock that is included (removed) to (from) an index. Further assume that the stock's and groups' returns are affected by a common fundamental return shock f_t, group-specific non-fundamental return shocks u_i, and idiosyncratic fundamental return shocks e_i. The assumptions result in the following expressions:

$$y_t = b_{yt} f_t + c_{1t} u_{1t} + c_{2t} u_{2t} + e_{yt}$$
$$x_{1t} = b_{1t} f_t + u_{1t} + e_{1t}$$

$$x_{2t} = b_{2t}f_t + u_{2t} + e_{2t}$$
$$var(e_{it}) = \sigma^2_{eit} \quad var(u_{it}) = \sigma^2_{uit} \quad var(f_t) = \sigma^2_{ft} \tag{1}$$

Further assume that the fundamental return shock is uncorrelated with the other shocks, that the group-specific non-fundamental shocks are uncorrelated across groups and that the idiosyncratic fundamental shock is uncorrelated with the non-fundamental shocks. That is, their covariances are equal to zero.

The theoretical predictions of the excess comovement hypothesis is that the loadings of stock y on the group-specific non-fundamental shocks, c_{1t} and c_{2t} in (1) will change as the stock changes groups. More specifically, for a stock that changes groups, with underbars representing loadings before the change and overbars representing loadings after the change, the predictions are:

$$\underline{c}_{1t} = \underline{c}_1 > 0 \qquad \underline{c}_{2t} = 0$$
$$\overline{c}_{1t} = 0 \qquad \overline{c}_{2t} = \overline{c}_2 > 0 \tag{2}$$

To put the expressions (2) in words, there is no loading on the group-specific non-fundamental shock to which the stock does not belong, and positive loading to the group which it does belong to. We further assume that the other parameters of the model are constant in each subperiod, which is before and after the event, but can vary across periods.

4.2 Economic magnitude

In the empirical analysis it is of interest to assess the economic magnitude of excess comovement. In other words, how much of the total variance of the event stock changes due to change in loading of the non-fundamental return shock, the change described in expressions (2). To describe this change, the following expressions before and after the event can be made:

$$\frac{\underline{c}_1^2 \underline{\sigma}_{u1}^2}{\underline{\sigma}_y^2} \quad and \quad \frac{\underline{c}_2^2 \underline{\sigma}_{u2}^2}{\underline{\sigma}_y^2} \tag{3}$$

These expressions are the results equal to the R-squared you would get if the stock's return was regressed against the non-fundamental component of the group's return. Similarly, the expressions for the fraction of group variance explained by the non-fundamental component are:

$$\frac{\overline{\sigma}_{u1}^2}{\overline{\sigma}_{x1}^2}, \quad \frac{\underline{\sigma}_{u1}^2}{\underline{\sigma}_{x1}^2}, \quad \frac{\overline{\sigma}_{u2}^2}{\overline{\sigma}_{x2}^2} \quad and \quad \frac{\underline{\sigma}_{u2}^2}{\underline{\sigma}_{x2}^2} \tag{4}$$

In the previous studies, three different regressions have been used. In Barberis et al (2005), one univariate and one bivariate and in Chen et al (2016), two univariate and one bivariate. In this study we will only consider the following two univariate regressions, the reasoning behind this choice will be elaborated further in sections 4.3 and 4.4. Thus, we will for now consider the following two regressions before and after the event:

$$y_t = \alpha + \beta_1 x_{1t} + \varepsilon_t \qquad\qquad y_t = \alpha + \beta_2 x_{2t} + \varepsilon_t \tag{5}$$

The probability limits for the regressions' slope coefficients are:

$$\beta_1 = \frac{cov(y_t, x_{1t})}{var(x_{1t})} \qquad\qquad \beta_2 = \frac{cov(y_t, x_{2t})}{var(x_{2t})} \tag{6}$$

Based on this model, the probability limits can in extension be written as:

$$\begin{aligned}
\underline{\beta}_1 &= \frac{\underline{b}_y \underline{b}_1 \underline{\sigma}_f^2 + \underline{c}_1 \underline{\sigma}_{u1}^2}{\underline{\sigma}_{x1}^2} & \overline{\beta}_1 &= \frac{\overline{b}_y \overline{b}_1 \overline{\sigma}_f^2}{\overline{\sigma}_{x1}^2} \\
\underline{\sigma}_{x1}^2 &= \underline{b}_1^2 \underline{\sigma}_f^2 + \underline{\sigma}_{u1}^2 + \underline{\sigma}_{e1}^2 & \overline{\sigma}_{x1}^2 &= \overline{b}_1^2 \overline{\sigma}_f^2 + \overline{\sigma}_{u1}^2 + \overline{\sigma}_{e1}^2 \\
\underline{\beta}_2 &= \frac{\underline{b}_y \underline{b}_2 \underline{\sigma}_f^2}{\underline{\sigma}_{x2}^2} & \overline{\beta}_2 &= \frac{\overline{b}_y \overline{b}_2 \overline{\sigma}_f^2 + \overline{c}_2 \overline{\sigma}_{u2}^2}{\overline{\sigma}_{x2}^2} \\
\underline{\sigma}_{x2}^2 &= \underline{b}_2^2 \underline{\sigma}_f^2 + \underline{\sigma}_{u2}^2 + \underline{\sigma}_{e2}^2 & \overline{\sigma}_{x2}^2 &= \overline{b}_2^2 \overline{\sigma}_f^2 + \overline{\sigma}_{u2}^2 + \overline{\sigma}_{e2}^2
\end{aligned} \tag{7}$$

An assumption consistent with the choice to look at an event without any fundamental effect, is to assume that all of the parameters, except the loadings on the non-fundamental component c_i, are constant over the subperiod:

$$\begin{aligned}
\underline{b}_i &= \overline{b}_i \equiv b_i & \underline{\sigma}_{ui}^2 &= \overline{\sigma}_{ui}^2 \equiv \sigma_{ui}^2 > 0 \\
\underline{\sigma}_{ei}^2 &= \overline{\sigma}_{ei}^2 \equiv \sigma_{ei}^2 & i &= 1, 2 \\
\underline{b}_y &= \overline{b}_y \equiv b_y & \underline{\sigma}_{ey}^2 &= \overline{\sigma}_{ey}^2 \equiv \sigma_{ey}^2 \\
\underline{\sigma}_f^2 &= \overline{\sigma}_f^2 \equiv \sigma_f^2 & &
\end{aligned} \tag{8}$$

The resulting predictions of the excess comovement hypothesis are the following:

$$\underline{\beta}_1 > \overline{\beta}_1 \quad and \quad \underline{\beta}_2 < \overline{\beta}_2 \tag{9}$$

To clarify, when the stock switches groups, it stops loading on the non-fundamental return shock of the old group which reduces its coefficient to the old group over the event. It then starts loading on the new group's non-fundamental return shock which increases the coefficient to the new group. The change in movement towards the different groups are thus explained by excess comovement, only loadings on the non-fundamental factor is responsible for the change in coefficients. Furthermore, the difference between the coefficients before and after the change can be expressed as:

$$\underline{\beta}_1 - \overline{\beta}_1 = -\frac{\underline{c}_1 \sigma_{u1}^2}{\sigma_{x1}^2} \quad and \quad \underline{\beta}_2 - \overline{\beta}_2 = \frac{\overline{c}_2 \sigma_{u2}^2}{\sigma_{x2}^2} \tag{10}$$

This is exactly the effect of economic significance that was sought after to isolate in (3). If the empirical results show a change of coefficients as in (10) there would be strong evidence for the hypothesis of comovement. If it is further assumed that the loadings on the non-fundamental factor is equal to one, $c_i = 1$, which on average is true since the non-fundamental shock of a group is a value-weighted average of their constituents, then the empirical results are quantifiable. Consequently, a 0,1 change in the beta would suggest that 10% of the group's variance is due to excess comovement. To summarize, the use of two univariate regressions before and after the event in an empirical analysis will be able to both isolate and quantify the effect of excess comovement.

4.3 Assumptions for a bivariate regression

In order to express predictions for the excess comovement hypothesis for a bivariate regression

$$y_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + \varepsilon_t \tag{11}$$

further assumptions than those made in the sections above have to be made, beyond the assumption that all parameters except the loading on the non-fundamental factor are constant over the subperiod (8). These are; the group returns have no idiosyncratic fundamental shock ($e_{12} = e_{22} = 0$), stock y have a non-fundamental shock loading of one ($c_1 = c_2 = 1$) and a unity of the loadings on the fundamental shocks ($b_y = b_1 = b_2 = 1$). These assumptions result in predictions comparable by those of Barberis et al (2005):

$$\underline{\beta}_1 = 1, \ \overline{\beta}_1 = 0, \qquad \underline{\beta}_2 = 0, \quad and \quad \overline{\beta}_2 = 1 \tag{12}$$

As discussed by Chen et al (2016), the problem with these predictions are that for economic significance we are not interested in the coefficients themselves. Instead, the coefficients are used to isolate the variance effects because of the non-fundamental loadings, demonstrated in (10). Therefore, with an assumption that the loadings on the fundamental and non-fundamental factors are equal across the groups and stock y, the coefficients of the bivariate regression are independent of the variances coming from the non-fundamental factor. These coefficients thus become economically meaningless as they can describe a dramatic change during a group switch without any way to quantify the meaning for excess comovement. Furthermore, since the two independent variables in the regression are highly correlated as they are returns of two well diversified portfolios, the ability to quantify the results are even more important.

Due to these problems, the bivariate regression is not used in this study. Since possible results would not be able to be interpreted in light of excess comovement, we deem using the bivariate regression to be uninformative. The problems of interpretation are also further described in sections 4.4.1 - 4.4.3 below.

4.4 Parameter instability

Even if the stylized model outlined above provides predictions about how excess comovement would be demonstrated in empirical results, it is not certain that the assumptions of parameter stability across subperiods (8) are true in reality. Chen et al (2016) contains a well-made numerical analysis of how changes in other parameters than the loading on the non-fundamental factor c_i would affect the coefficients of the regressions. To test the effect, they assume that there is no excess comovement and then stimulate changes in the other parameters separately. The changes in parameters are (1) changes to the fundamental beta of the stock, (2) changes in the idiosyncratic risk of group returns and (3) changes in the fundamental betas of group returns, respectively.

For brevity, the full numerical examples will not be included in this study since these are accessible in Chen et al (2016). However, for the cohesion of this paper, to further explain the choice to disregard the bivariate regression and to explain the choice to create a matched sample of stocks, we will provide the conclusions made by Chen et al (2016) below.

4.4.1 Change in stocks fundamental beta

When changing the fundamental loading b_y of stock y within the subperiod, regression coefficients towards both group returns will increase. This can be interpreted as that the stock moves more with the market in general and not with a specific group. For the univariate regression the percentage change shows up almost one for one in the difference of the two pairs of coefficients (10). In the bivariate regression the change is essentially the same but equally split between the two differences of coefficients.

4.4.2 Change in idiosyncratic risk of group returns

When changing the idiosyncratic volatility, e_i, of one of the groups within the subperiod, the change in the univariate regression shows as a small difference between the first coefficients towards that group's return and has no effect on the second difference of coefficients (10). For the bivariate regression however, the effect is much larger. With only a small change of volatility of the first group, the regression shifts substantial weight to the other groups return resulting in a, relative to the univariate change, roughly five times as large negative change in difference of the first pair coefficients and roughly five times as large positive change in difference of the second pair of coefficients. If a pattern were to be identified between the changes of the two regressions, a change of half as much as in 4.4.1 would be expected. As no comovement is present in this model, these spurious effects affect the ability to quantify economic significance for the bivariate regression negatively, while only having small effects on the univariate regression.

4.4.3 Change in groups fundamental beta

When changing the fundamental beta of group returns, the change shows in the univariate regression roughly one to one in difference of the coefficients towards the group return whose beta has changed, while the other difference of coefficients are unchanged. Assuming that the beta change is negative, the following interpretation is that when the group return is less sensitive to the fundamental factor, the loading of the stock toward that group's return must increase to compensate for this decrease. For the bivariate regression, the change results in a smaller increase in the loading of the unchanged group as the changed group becomes a poorer proxy for return. To summarize the effects on the bivariate regression, no easily interpretable pattern can be recognized as for the univariate regression, which further supports the disregard of the bivariate regression.

4.4.4 Matched sample approach

The above sections 4.4.1 - 4.4.3 show that the instability of parameters can result in effects in the coefficients by changes in parameters not related to excess comovement. For an empirical analysis outside a stylized model, it can therefore be troublesome to distinguish between effects caused by excess comovement and these other changes. Of course, it could be possible to try to identify patterns in changes that correspond to changes seen in 4.4.1 - 4.4.3, yet such analysis would be uncertain in light of the complexity of real-world data. There is however a possibility for a matched sample approach to isolate the effect of excess comovement. Since the changes of group parameters in section 4.4.2 and 4.4.3 will show up in a regression regardless of the identity of the stock regressed as the dependent variable, the fundamental changes described in 4.4.1 is what needs to be matched with another sample. That is, a sample of stocks that match the change in fundamental loading without being exposed for an index event will allow isolation of the excess comovement effect. We further describe the method of this approach in section 5.4.

5. Empirical method

5.1 Data

Since this study aim to extend the studies of comovement on index changes to the Swedish stock market, an index corresponding to the S&P 500 in Sweden needs to be chosen. The most suitable index with regards to the objective of S&P 500 to reflect large-cap stocks in the U.S., would be the OMXS30 index. However, since the OMXS30 consists of a smaller amount of stocks, results could lack significance when the amount of index events are fewer. Therefore, the OMX Stockholm Benchmark is chosen instead. This index satisfies the requirements that Barberis et al (2005) use to choose the S&P 500; the group is a natural category or preferred habitat for investors, it has clear and identifiable changes in membership and lastly, the changes in membership should not affect the asset's fundamental value. For indexing, which is a relevant and possible source of excess comovement (Chen et al, 2016), there are approximately 68 billion SEK invested in passive index funds that follow the OMXSB compared to the approximately 24 billion SEK following the OMXS30 (Morningstar, 2020). In this aspect, OMXSB show sufficient evidence for indexing, if not better, to that of the OMXS30.

Regarding index event data, biannually official press releases from NASDAQ are gathered from the Dow Jones Factiva database and constituents analysis from the Thomson Reuters Eikon database. Daily data of stock prices, market value and turnover are mainly collected from Thomson Reuters Datastream yet complemented with data from the Swedish House of Finance database Finbas. Historical prices of the OMXSB and OMXSPI, index of all shares registered on the SSE, are collected from the NASDAQ OMX Nordic website and the market capitalization of the indices are collected from the Thomson Reuters Datastream.

The collection of samples resulted in 132 inclusions and 116 removals. After adjusting for new issues and de-listings close to the event date, by requiring 252 days of data before and after the event window, the samples are reduced to 101 inclusions and 87 removals. This length of available data also corresponds to the required length of data to conduct the matched sample approach.

Barberis et al (2005) use three data frequencies, daily, weekly and monthly. Chen et al (2016) mainly use daily data for their analysis, since they find that the different frequencies of Barberis et al (2005) show similar results yet more significantly at a daily frequency. Therefore, the daily frequency is the only one used in this paper.

5.1.1 Time period

In 2007, NASDAQ acquired the OMX indices in the Nordics. Due to this, we are not able to find any original press releases about index events before the acquisition. Without another trustworthy source of the correct event stocks and announcement dates, this limit the start of our time period to 2007. Furthermore, Chen et al (2016) as well as Barberis et al (2005) exclude data from October 1987 in their sample. This was a month characterized by economic turbulence, resulting in the black Monday. We see the financial crisis in 2008 as a similar period of economic downturn. However, the market fell in the end of 2007 as well as in 2008, for several months. Since this is in the very beginning of our dataset, we choose to exclude both those years and start our time period in June 2009. Furthermore, the last daily price data used is in January 2020, which also excludes the downturn caused by COVID-19. The length of our total time-period corresponds to one sub-period in Barberis et al (2005) and Chen et al (2016). They mainly analyze their results from a sub-period perspective, which indicates that the length of our period is of use for analysis.

5.2 Univariate regressions

The two univariate regressions described in equation (5) are run with OLS estimation in the pre- and post-event period for each individual stock in our four samples. The two independent variables used are the two group returns, index return and non-index return. To account for time effects, standard errors has been clustered by month as in the two previous studies (Barberis et al, 2005 and Chen et al, 2016). The mean loading of all stocks in each sample towards each of the two independent variables are recorded together with their standard errors. For the Dimson (1994) adjustment, the same regressions with added leads and lags are used with its coefficients summed. To determine the statistical significance of the result the t-statistic of each mean is calculated. In order for the results to be statistically significant at a 1%, 5% and 10% level we require a t-statistic of 2.576, 1.960 and 1.645, respectively. For simplicity we thus assume that the degrees of freedom are infinite.

We run these regressions on daily data frequencies. The pre-event regressions are run over the last 252 trading days, starting 20 trading days before implementation date and the post-event regressions are run over the preceding 252 trading days, starting two days after implementation date. This timeframe corresponds to the one used by Barberis et al (2005) and Chen et al (2016) at the daily frequency.

In our sample, announcement dates have occurred within one month before the implementation date. To avoid the issue of deciding whether the to-be-added stock should be included in the index or not between the announcement and implementation date, we do not use data in between those dates. This corresponds to the method of Barberis et al (2005) and Chen et al (2016).

5.3 Return of the non-index group

Since the two independent variables used in our regressions are the index return and the non-index return, the latter need to be calculated as it is not available to gather directly. The method for this is to use the total return of stocks on the exchange, OMXSPI and subtract the portion contributed by index stocks, the OMXSB, to get the non-index return.

For the calculation, daily data of prices and market capitalization for OMXSB ($R_{B,t}$) and OMXSPI (R_{PI}) are obtained. To calculate the return of non-OMXSB stocks ($R_{nonB,t}$), we use a calculation presented by Barberis et al (2005) shown below:

$$R_{PI} = \left(\frac{CAP_{PI,t-1} - CAP_{B,t-1}}{CAP_{PI,t-1}}\right) R_{nonB,t} + \left(\frac{CAP_{B,t-1}}{CAP_{PI,t-1}}\right) R_{B,t} \qquad (13)$$

Solving for $R_{nonB,t}$, the equation is as follows:

$$R_{nonB,t} = \frac{R_{PI} - \left(\frac{CAP_{B,t-1}}{CAP_{PI,t-1}}\right) R_{B,t}}{\frac{CAP_{PI,t-1} - CAP_{B,t-1}}{CAP_{PI,t-1}}} \qquad (14)$$

Where $CAP_{B,t-1}$ is the market capitalization for the OMXSB index in period $t - 1$ and $CAP_{PI,t-1}$ is the market capitalization for the OMXSPI index in period $t - 1$.

5.4 Matching stock sample

In order to choose matching stocks for event stocks, we use the same method as Chen et al (2016). First, one-year cumulative return is calculated for all stocks in the sample at each inclusion date. All of the stocks are also sorted into size deciles based on the market capitalization value of the companies at this date. Lastly, at inclusion date each stock is classified as either an OMXSB-stock or a non-OMXSB stock. For each event stock, a matching stock is chosen based on having the most similar one-year cumulative return while being in the same size decile yet not subject to the same event as the event stock. In other words, a matching stock for a joining event stock is not included and do not join the OMXSB index, and a matching stock for a leaving event stock is included and do not leave the OMXSB index.

5.4.1 Limitations

Since some event stocks have performed extraordinarily, either very well (joiners) or very bad (leavers) in terms of yearly return, it is not always possible to find a matching stock. Another issue is that there is not always a stock in the same size decile as the event stock, which prevents the choosing of a matching stock. This is opposed to Chen et al, who finds matching for all event stocks, although not perfect matches. An explanation for this difference is that we have fewer stocks in each size decile to choose matching stocks from due to the smaller amount of stock listed on the exchange. The implications of choosing matching stocks results in differences of returns in our samples. The mean and median yearly return for joiners is 42,29% and 24,57%, respectively, while for joiners matching stocks 26,70% and 21,48%. For leavers the mean and median are -3,40% and -2,05%, while leavers matching stocks had -1,50% and -2,97%. Chen et al (2016) does not specify the means and medians of their samples, only that joiners in the top 10% return decile have significantly higher returns than their matched stocks, which is similar to that of our samples.

6. Empirical results and analysis

6.1 Univariate regression results

The first step of our analysis is to estimate the two univariate regressions described in equation (5) and presented in Table 1. The regressions are run on our samples of joiners and leavers with one regression in each sub-period. The univariate regression on the group that the stock is leaving was first made in the study made by Chen et al (2016) and has in previous studies only been made on the group that the stock is joining.

In Panel A the results of the joining OMXSB stocks are presented while Panel B contains results of the leaving stocks for the period. In Panel A the first three columns contain the betas towards the old group (non-index stocks) before and after the event with the associated changes. The second three columns similarly contain the betas towards the new group while the last column contain the difference of the two differences. Panel B describes the betas in the same way, except that the groups are in different order since the leaving and joining group for these stocks are in opposite order. Thus, for both panels, the group that the stock is leaving is in the left columns while the group that the stock is joining is to the right.

Table 1.
OMXSB additions and removals

The following regressions are estimated

$$y_t = \alpha + \beta_1 x_{1t} + \varepsilon_t \qquad\qquad y_t = \alpha + \beta_2 x_{2t} + \varepsilon_t$$

for two samples of stocks that are added or removed from the OMXSB index in the period 2009-2019. The pre-event estimation window consists of 252 trading days prior to 20 trading days before the event, while the post-event consists of 252 trading days, 2 trading days after the event of inclusion/removal. x_{1t} *and* x_{2t} *is the daily return of the group the stock is leaving and the group the stock is joining at time t respectively. The rate of return of OMXSB stocks are calculated using daily prices and market capitalization data obtained from Thomson Reuters Eikon. To calculate the rate of return of capitalization-weighted index of the non-OMXSB stocks we used a method introduced by Barberis et al (2005), described in equation (14). The regressions were OLS estimated separately for each stock for each estimation period with standard error clustered by month. The values on the first row is their mean and the values on the second row is the t-statistic. Panel A shows coefficients of the joining stocks and Panel B shows coefficients for leaving stocks.*

Panel A: Univariate regressions for joiners								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	101	0,948	1,001	0,053	0,788	0,851	0,063	0,010
		26,985	26,943	1,898	25,066	25,743	2,381	1,207
Panel B: Univariate regressions for leavers								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	87	0,767	0,744	-0,024	0,884	0,887	0,003	0,027
		23,621	21,193	-0,871	24,999	22,570	0,106	3,687

Starting with analysis of panel A with joining stocks, we can see that the 0,063 positive change of β_2 is statistically significant at the 5% level. Looking at prediction (10), this is evidence for the excess comovement hypothesis, and the conclusion quantified is that 6,3% of total variance is due to excess comovement. However, the same hypothesis predict that the change in β_1 is negative, which our results do not show. The 0,053 positive change of β_1 is significant at the 10% level and together with the result of the total comovement,

$\Delta\beta_2 - \Delta\beta_1$, that is statistically insignificant different from zero, the excess comovement hypothesis is not supported. Instead, which is also the conclusion of Chen et al (2016), our results indicate that there has been a change in fundamental beta for these stocks, the change described in 4.4.1. For further support of this hypothesis, the analysis continues in 6.2.

As for panel B and leaving stocks, the results support the prediction made by the excess comovement hypothesis in (10). The change of the beta towards the group that the stocks are leaving, $\Delta\beta_1$, is negative at the same time as the change of beta towards the joining group, $\Delta\beta_2$, is positive. However, these changes are not statistically significant even if the total amount of comovement, $\Delta\beta_2 - \Delta\beta_1$, at 0,027 is statistically significant at a 1% level. Thus, these results provide tendencies of the excess comovement hypothesis, yet they are not statistically strong. Since $\Delta\beta_1$ and $\Delta\beta_2$ is not significantly different from zero, that will be our defensively taken conclusion from these results. Chen et al (2016) do not tabulate their results from their sample of leaving stocks, yet they claim that the results are equal but opposite to the joining stocks sample. In other words, both $\Delta\beta_1$ and $\Delta\beta_2$ are negative and statistically significant.

6.2 Regressions with a matched sample approach

As discussed in 4.4.4, an approach to differentiate the effect from excess comovement to other changes of parameters, is the matched sample approach. The aim of the approach is to match event stocks to other stocks with the same change of fundamental beta. For change of fundamental beta, momentum has proved to be a crucial variable in studies by Jegadeesh and Titman (2001), Chen et al (2016) and Kasch and Sarkar (2014). The last two of these studies have shown correlation between momentum and index changes, joiners are often found in top deciles while leavers are found in bottom deciles. Due to momentum then, these are also subject to fundamental beta changes, especially strong for winners in the top two deciles but also with a negative effect for losers in the bottom two (Chen et al 2016). For the Swedish market and the OMXSB index our results show that there is an equal tendency. The sample of stocks joining the index are most commonly found in the top 3 deciles (54,10%), while the leaving stocks have the analogous frequency in the bottom 4 deciles (55,20%) as can be seen in Table 2.

Table 2

Momentum deciles.

Based on the methodology of Jegadeesh and Titman (2001) and Chen et al (2016), momentum deciles are created for all stocks based on their one-year cumulative rate of return preceding each implementation date. Stocks in the first decile are stocks that performed the worst out of all the stocks, and hence named as losers. Stocks in the tenth decile are stocks that performed best out of all the stocks, and hence named as winners. The second and third columns are the event stocks, and the fourth and fifth columns are the matching stock samples. The first sub-column under each column is the percentage portion of the sample that is attributed to each decile, and the second sub-column is the cumulative percentage.

	Frequency							
	Joiners		Leavers		Joiners matching stock		Leavers matching stock	
Decile	%	*Cum. %*	%	*Cum. %*	%	*Cum. %*	%	*Cum. %*
Losers	0,90	*0,90*	17,10	*17,10*	2,90	*2,90*	13,80	*13,80*
2	6,40	*7,30*	12,40	*29,50*	5,80	*8,70*	13,80	*27,50*
3	5,50	*12,80*	14,30	*43,80*	5,80	*14,40*	11,20	*38,80*
4	8,30	*21,10*	11,40	*55,20*	8,70	*23,10*	11,20	*50,00*
5	5,50	*26,60*	13,30	*68,60*	7,70	*30,80*	13,80	*63,80*
6	4,60	*31,20*	6,70	*75,20*	3,80	*34,60*	10,00	*73,80*
7	14,70	*45,90*	9,50	*84,80*	14,40	*49,00*	11,20	*85,00*
8	9,20	*55,00*	5,70	*90,50*	15,40	*64,40*	8,80	*93,80*
9	26,60	*81,70*	7,60	*98,10*	22,10	*86,50*	5,00	*98,80*
Winners	18,30	*100,00*	1,90	*100,00*	13,50	*100,00*	1,20	*100,00*

With a matched sample approach, concurrent changes of fundamental beta due to momentum can be identified by creating a matched sample described in 5.4. As can be seen in Table 2, the decile frequency distribution of the matched samples approximately match the two original samples, with differences stemming from limitations mentioned in 5.4.1.

The second step of our analysis is therefore to use our two univariate regressions on our two matched samples. In Table 3 the joiner stocks as in 6.1 are presented in panel A, the matched sample for joiners in panel B and the differences between their coefficients in panel C.

Table 3

Changes in beta of stocks included in the OMXSB index relative to matching stocks

The following regressions are estimated

$$y_t = \alpha + \beta_1 x_{1t} + \varepsilon_t \qquad y_t = \alpha + \beta_2 x_{2t} + \varepsilon_t$$

for a sample of stocks that are added to the OMXSB index. Analogous regressions are run for each matching stocks that are in the same size decile and have a similar yearly rate of return during the pre-event estimation window as the event stock but that is not included in the OMXSB index. Both regressions are run in the period 2009-2019. The pre-event estimation window consists of 252 trading days prior to 20 trading days before the event, while the post-event consists of 252 trading days, 2 trading days after the event of inclusion/removal. x_{1t} and x_{2t} is the daily return of the group the stock is leaving and the group the stock is joining at time t respectively. The rate of return of OMXSB stocks are calculated using daily prices and market capitalization date obtained from Thomson Reuters Eikon. To calculate the rate of return of capitalization-weighted index of the non-OMXSB stocks we used a method introduced by Barberis et al (2005), described in equation (14). To find the event stocks changes in beta relative to their matching stocks, we run regressions from the difference between the beta of the event stock and matched stock for all stocks and for each event window. The regressions were OLS estimated separately for each stock for each estimation period with standard error clustered by month, the values on the first row is their mean and the values on the second row is the t-statistic.

Panel A shows coefficients of the event stocks, panel B for matched stocks and panel C the differences between the samples..

Panel A: Univariate regressions for joiners								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	101	0,948	1,001	0,053	0,788	0,851	0,063	0,010
		26,985	26,943	1,898	25,066	25,743	2,381	1,207
Panel B: Univariate regressions for joiners matching stock								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	94	0,817	0,886	0,069	0,683	0,746	0,063	-0,006
		21,420	22,259	1,905	20,386	21,139	1,992	-0,647
Panel C: Differences of coefficients between event stock sample and matched stock sample								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	101	0,132	0,115	-0,017	0,105	0,105	0,000	0,016
		2,752	2,165	-0,370	2,517	2,190	-0,008	1,425

Looking at panel B with the results from the matching stock sample, we see an almost equal change in the beta towards both groups, $\Delta\beta_1$ and $\Delta\beta_2$, as for our sample of event stocks, which is statistically significant at the 10% and 5% level respectively. Since the matched sample has not experienced the index event, this implies that the changes of the beta towards the groups is due to fundamental change described in 4.4.1 rather than non-fundamental factors, thus not supporting the excess comovement hypothesis. In fact, we do not see any differences in changes with statistical significance difference from zero in Panel C, which means that the excess comovement hypothesis is not supported when controlling for momentum, also in the Swedish market. This is in line with results from Chen et al (2016) for the S&P 500, even if they do not tabulate results with solely the matched sample treatment. Their tabulation of the matched sample is together with the Dimson adjustment, which we will show in 6.3.

An interesting point is the higher absolute level of beta in the event stock sample compared to the matched sample. This difference is also in line with the results of Chen et al (2016) who show only slightly lower differences than ours of approximately 0,11, those in column 1, 2, 4 and 5 in Panel C. Perhaps there is a tendency for stocks with more loading on the fundamental factor to join an index, but since this study aims to look at the excess comovement effect of the index event, it is only the changes of beta that are relevant. The difference in absolute levels is therefore not investigated but simply noted.

The matched sample approach is tabulated for the leaver sample in Table 4. Panel A is the same as Panel B of Table 1 in section 6.1, Panel B is the results for the matched sample for leaving stocks and Panel C is the difference of coefficients between the samples.

Table 4
Changes in beta of stocks removed from the OMXSB index relative to matching stocks

The following regressions are estimated

$$y_t = \alpha + \beta_1 x_{1t} + \varepsilon_t \qquad y_t = \alpha + \beta_2 x_{2t} + \varepsilon_t$$

for a sample of stocks that are removed from the OMXSB index. Analogous regressions are run for each matching stock that are in the same size decile and have a similar yearly rate of return during the pre-event estimation window as the event stock but that is not removed from the OMXSB index. Both regressions are run in the period 2009-2019. The pre-event estimation window consists of 252 trading days prior to 20 trading days before the event, while the post-event consists of 252 trading days, 2 trading days after the event of inclusion/removal. x_{1t} *and* x_{2t} *is the daily return of the group the stock is leaving and the group the stock is joining at time t respectively. The rate of return of OMXSB stocks are calculated using daily prices and market capitalization date obtained from Thomson Reuters Eikon. To calculate the rate of return of capitalization-weighted index of the non-OMXSB stocks we used a method introduced by Barberis et al (2005), described in equation (14). To find the event stocks changes in beta relative to their matching stocks, we run regressions from the difference between the beta of the event stock and matched stock for all stocks and for each event window. The regressions were OLS estimated separately for each stock for each estimation period with standard error clustered by month, the values on the first row is their mean and the values on the second row is the t-statistic. Panel A shows coefficients of the event stocks, panel B for matched stocks and panel C for the differences of coefficients between the samples.*

Panel A: Univariate regressions for leavers								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	87	0,767	0,744	-0,024	0,884	0,887	0,003	0,027
		23,621	21,193	-0,871	24,999	22,570	0,106	3,687
Panel B: Univariate regressions for leavers matching stock								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	81	0,758	0,765	0,007	0,874	0,891	0,017	0,010
		21,285	20,637	0,356	22,188	21,344	0,733	1,484
Panel C: Differences of coefficients between event stock sample and matched stock sample								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	87	0,009	-0,022	-0,031	0,010	-0,004	-0,014	0,017
		0,228	-0,450	-1,015	0,229	-0,077	-0,425	1,728

In Panel B no statistically significant results of changes in betas can be found. Interestingly however, is that the corresponding direction of changes to the excess comovement hypothesis as in Panel A, is not the same in Panel B. Still, without statistical significance different from zero it is not possible to draw a strong conclusion from this, except, again, that there are little yet not strong tendencies for the excess comovement hypothesis. The total amount of comovement between the two samples, $\Delta\beta_2 - \Delta\beta_1$, is in fact statistically significant at the 10% level, with an amount corresponding to 1,7% of total variance. In what direction however, results are not strong enough to say.

In order to explain the lack of statistically significant results from our leaving samples, we find two explanations most plausible. The first is that momentum effects seem to be much stronger for winners than losers. According to the momentum portfolio formation by Chen et al (2016) with the recording of changes of betas during a two year period, one year before and after formation, winners in the top two deciles show approximately four times as large positive change of fundamental beta as the negative change of fundamental beta for losers in the bottom two deciles. The remaining middle deciles show practically no change of fundamental beta. Thus, when assuming that there is only an effect from momentum and no excess comovement, we should have better chances observing significant results in the sample with winners than the one with losers. The second explanation is that our joining-sample contains a higher concentration of stocks in these top two deciles (45,00%) than the concentration of stocks in the bottom two deciles in the leaving sample (29,50%), see Table 2. When more of these samples consist of middle deciles not contributing to a change in beta, significant results should be harder to find.

To find an explanation of the difference in concentrations, a comparison with prior studies would be interesting. Unfortunately, Chen et al (2016) does not tabulate their results for leaving stocks which complicates a comparison. What they do say is that they expect weaker results with a smaller sample with firms potentially undergoing structural changes, yet that their results show equal but opposite results as the joining sample at a significant level. Potentially, a conclusion could therefore be made that return performance is generally worse for index leavers in the US than in Sweden. In other words, the mechanical qualification or disqualification of OMXSB could potentially lower the bar of the negative performance needed to be excluded from the index compared to the same for the S&P 500.

6.3 Regressions with Dimson adjustment and matched sample approach

To find explanations of which friction- or sentiment-based hypothesis that is responsible for the effect of excess comovement, Barberis et al (2005) use a method introduced by Dimson (1979), where the coefficients in a regression where leads and lags are included. This should unfold a better estimation of the beta coefficient of a stocks return towards the group returns. Chen et al (2016) replicates the method of Barberis et al (2005) and our results with the adjustment as well as the matched sample approach are presented in Table 5 below.

Table 5.
OMXSB index additions with Dimson adjustment and matched sample approach

The following regressions are estimated

$$y_t = \alpha + \sum_{s=-2}^{2} \beta_1^s x_{1,t+s} + \varepsilon_t \qquad\qquad y_t = \alpha + \sum_{s=-2}^{2} \beta_1^s x_{2,t+s} + \varepsilon_t$$

for a sample of stocks that are added to the OMXSB index. Analogous regressions are run for matching stocks that are in the same size decile and the most similar yearly rate of return during the pre-event estimation window as the event stock but that was not included to the OMXSB index. Both regressions are run in the period 2009-2019. The pre-event estimation window consists of 252 trading days prior to 20 trading days before the event, while the post-event consists of 252 trading days, 2 trading days after the event of inclusion/removal. x_{1t} and x_{2t} is the daily return of the group the stock is leaving and the group the stock is joining at time t respectively. To find the event stocks changes in beta relative to their matching stocks, we ran regressions from the difference between the beta of the event stock and matched stock for all stocks and for each event window. The Dimson beta is defined as a simple sum of the lag and lead coefficients from the regressions above with two leads and lags. The regressions were OLS estimated separately for each stock for each estimation period with standard error clustered by month, the values on the first row is their mean and the values on the second row is the t-statistic. Panel A shows changes in beta from the event stocks, panel B from matched stocks and panel C for the differences in coefficients between the two samples.

Panel A: Univariate regressions for joiners with Dimson adjustment								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\boldsymbol{\beta_1}$	β_1	β_2	$\Delta\boldsymbol{\beta_2}$	$\Delta\boldsymbol{\beta_2} - \Delta\boldsymbol{\beta_1}$
2009-2019	101	1,033	1,175	0,141	0,918	1,051	0,133	-0,008
		22,806	22,534	2,655	19,927	21,305	2,585	-0,352

Panel B: Univariate regressions for joiners matching stock with Dimson adjustment								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\boldsymbol{\beta_1}$	β_1	β_2	$\Delta\boldsymbol{\beta_2}$	$\Delta\boldsymbol{\beta_2} - \Delta\boldsymbol{\beta_1}$
2009-2019	94	0,891	0,978	0,087	0,779	0,898	0,120	0,033
		19,254	16,056	1,276	17,749	15,779	1,897	1,585

Panel C: Differences coefficients between event stock sample and matched stock sample with Dimson adjustment								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\boldsymbol{\beta_1}$	β_1	β_2	$\Delta\boldsymbol{\beta_2}$	$\Delta\boldsymbol{\beta_2} - \Delta\boldsymbol{\beta_1}$
2009-2019	101	0,142	0,197	0,054	0,139	0,152	0,013	-0,041
		2,363	2,750	0,636	2,413	2,299	0,174	-1,367

Starting with a general conclusion of our results with a Dimson adjustment, it can once again be concluded, as in the previous section, that we find no support of the excess comovement hypothesis with the matched sample approach. Looking at Panel C, we find no statistically significant results for differences between our event and matched sample.

There is however an interesting difference between our results and the two previous studies. Looking at panel A, we find increased changes in both betas, $\Delta\beta_1$ and $\Delta\beta_2$, compared to results without the adjustment. This result is opposite what was found by Chen et al (2016) and Barberis et al (2005). They saw that the absolute value of the betas increased after the adjustment, which we also did, yet they saw a higher increase of beta in the pre-inclusion period than in the post-inclusion period. Both studies therefore saw a reduced $\Delta\beta_1$ and $\Delta\beta_2$ of approximately one third. With the notion that turnover is lower in the pre-inclusion period than after, Barberis et al (2005) attribute this effect to the information diffusion hypothesis while Chen et al (2016) do not dare to agree since they suggest that microstructures such as non-synchronous trading also could be attributable.

Our results of increasing differences therefore support the suggestion of Chen et al (2016) of a microstructure effect instead of the information diffusion claim by Barberis et al (2005). The larger increase of post-inclusion beta compared to the pre-inclusion beta indicates that autocorrelation is higher after the introduction to the index, opposite to what the information diffusion hypothesis predicts. This autocorrelation increase is present even if we find that the mean turnover of our event stocks is higher after inclusion than before, which means that there must be another microstructure effect present on the Swedish market.

Even if the subject has not been thoroughly investigated, an explanation can be found in the working paper of Säfvenblad (1997) which concludes that the autocorrelation of short-term returns in the Swedish market is attributable to a combination of non-synchronous trading and profit-taking. One of the effects of profit-taking that Säfvenblad finds is autocorrelation-asymmetry with higher autocorrelation for days with higher returns and lower autocorrelation for days with lower returns. Together with a sample of stocks that is concentrated in high momentum deciles and concurrent high positive returns, profit-taking is a probable explanation of our results that show higher autocorrelation in the post-inclusion period. Thus, the difference in results is most likely due to differences in microstructures between the US and Swedish markets.

Important to note is that despite the difference between our and the two previous studies results, the matched sample approach still do not show support of the excess comovement hypothesis. Next, we turn to the results of our leaving samples with a Dimson adjustment in Table 6.

Table 6.
OMXSB index removals with Dimson adjustment and matched sample approach

The following regressions are estimated

$$y_t = \alpha + \sum_{s=-2}^{2} \beta_1^s x_{1,t+s} + \varepsilon_t \qquad y_t = \alpha + \sum_{s=-2}^{2} \beta_1^s x_{2,t+s} + \varepsilon_t$$

for a sample of stocks that are removed from the OMXSB index. Analogous regressions are run for matching stocks that are in the same size decile and the most similar yearly rate of return during the pre-event estimation window as the event stock but that is included in the OMXSB index. Both regressions are run in the period 2009-2019. The pre-event estimation window consists of 252 trading days prior to 20 trading days before the event, while the post-event consists of 252 trading days, 2 trading days after the event of inclusion/removal. x_{1t} *and* x_{2t} *is the daily return of the group the stock is leaving and the group the stock is joining at time t respectively. To find the event stocks changes in beta relative to their matching stocks, we ran regressions from the difference between the beta of the event stock and matched stock for all stocks and for each event window. The Dimson beta is defined as a simple sum of the lag and lead coefficients from the regressions above with two leads and lags. The regressions were OLS estimated separately for each stock for each estimation period with standard error clustered by month, the values on the first row is their mean and the values on the* *second row is the t-statistic. Panel A shows changes in beta from the event stocks, panel B from matched stocks and panel C for the differences in coefficients between the two samples.*

Panel A: Univariate regressions for leavers with Dimson adjustment								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\boldsymbol{\beta_1}$	β_1	β_2	$\Delta\boldsymbol{\beta_2}$	$\Delta\boldsymbol{\beta_2} - \Delta\boldsymbol{\beta_1}$
2009-2019	87	0,948	0,909	-0,039	1,018	1,022	0,004	0,043
		19,727	16,247	-0,616	21,109	16,945	0,063	2,450

Panel B: Univariate regressions for leavers matching stock with Dimson adjustment								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\boldsymbol{\beta_1}$	β_1	β_2	$\Delta\boldsymbol{\beta_2}$	$\Delta\boldsymbol{\beta_2} - \Delta\boldsymbol{\beta_1}$
2009-2019	81	0,893	0,923	0,029	0,961	1,020	0,059	0,030
		18,694	19,020	0,525	20,504	19,696	1,060	1,459

Panel C: Differences of coefficients between event stock sample and matched stock sample with Dimson adjustment								
		OMXSB			**Non-OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\boldsymbol{\beta_1}$	β_1	β_2	$\Delta\boldsymbol{\beta_2}$	$\Delta\boldsymbol{\beta_2} - \Delta\boldsymbol{\beta_1}$
2009-2019	87	0,055	-0,014	-0,068	0,057	0,002	-0,055	0,013
		0,818	-0,193	-0,795	0,868	0,028	-0,618	0,513

For the central test of the excess comovement hypothesis, the Dimson adjustment does not change the conclusion or discussion for the leaving samples in the previous section as we find no statistically significant differences in Panel C.

Building on the previous discussion of profit-taking as an explanation for the changes of betas found when making the adjustment, results from the leaving samples are ambiguous. Against the OMXSB, the betas of Panel A increased more in the pre-removal period than in the post-removal period which would support the profit-taking hypothesis. Changes against non-OMXSB and those for the matched sample, however, show equal changes and changes in the same direction as for the joiners respectively. The changes are relatively much smaller and again the problems with weaker momentum effects for losers and concentration of the samples are plausible explanations for the lack of a pattern found in the results. Due to these problems, microstructure differences are neither proved or disproved from the Table 6 results.

6.4 Mechanical qualification and pre-trading

The transparency of the OMXSB mechanical qualification provides the possibility for investors to anticipate the upcoming changes to the index, possibly before the announcement date. Chen et al (2016) and Barberis et al (2005) both make sure to exclude the time period when it is not certain if event stocks are traded as pre- or post-event, in other words, the time between announcement date and implementation date. In this section we therefore extend our excluded time period as a robustness check to make sure that no pre-trading has neglected findings of support for the excess comovement hypothesis. If it has, an extension of the excluded time period would for the sample of joining event stocks increase $\Delta\beta_2$ and decrease $\Delta\beta_1$. The results of the robustness check can be found in Table 7 Panel B while the results from the original event window is presented in Panel A.

Table 7.
Pre-trading robustness check for the sample of added stocks

The following regressions are estimated

$$y_t = \alpha + \beta_1 x_1 + \varepsilon_t \qquad\qquad y_t = \alpha + \beta_2 x_2 + \varepsilon_t$$

for one sample of stocks that are added to the OMXSB index in the period 2009-2019. The pre-event estimation window consists of 252 trading days prior to 20 trading days before the event in Panel A and 41 trading days before the event in Panel B, while the post-event consists of 252 trading days, 2 trading days after the event of inclusion/removal for both panels. x_{1t} and x_{2t} is the daily return of the group the stock is leaving and the group the stock is joining at time t respectively. The rate of return of OMXSB stocks are calculated using daily prices and market capitalization date obtained from Thomson Reuters Eikon. To calculate the rate of return of capitalization-weighted index of the non-OMXSB stocks we used a method introduced by Barberis et al (2005), described in equation (14). The regressions were OLS estimated separately for each stock for each estimation period with standard error clustered by month. The values on the first row is their mean and the values on the second row is the t-statistic. Panel A shows coefficients of the regressed sample with 21 days event window and Panel B shows coefficients of the same regressed sample with 42 days event window.

Panel A: Univariate regressions for joiners								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	101	0,948	1,001	0,053	0,788	0,851	0,063	0,010
		26,985	26,943	1,898	25,066	25,743	2,381	1,207
Panel B: Univariate regressions for joiners with extended event window								
		Non-OMXSB			**OMXSB**			**Diff. of diff.**
Period	**nobs**	β_1	β_2	$\Delta\beta_1$	β_1	β_2	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
2009-2019	100	0,932	1,002	0,070	0,778	0,851	0,074	0,004
		27,412	26,709	2,493	25,463	25,508	2,875	0,437

After increasing the event window to 42 days, both $\Delta\beta_1$ and $\Delta\beta_2$ increase at approximately equal amounts which does not support the hypothesis of pre-trading affecting our previous results. The total amount comovement $\Delta\beta_2 - \Delta\beta_1$ was even less statistically significant with the adjustment. Instead, the effect is more likely attributed to the missing increased loading on the fundamental factor these stocks experience from momentum when excluding two months instead of one. Therefore, our conclusions from previous sections can be seen as robust.

7. Conclusions

To extend the studies conducted by Barberis et al (2005) and Chen et al (2016) evaluating if index events are a source of excess comovement, we apply their methods on the Swedish market and the OMXSB. Due to the problem of quantifying the economic significance of the bivariate regression, we only use the two univariate regressions, combined with a matched sample approach similar to that of Chen et al (2016) and the Dimson adjustment used by both Barberis et al (2005) and Chen et al (2016). Furthermore, we conduct a robustness test if pre-trading has any implications on excess comovement for an index with a mechanical qualification process.

We find that, when estimating coefficients on our sample of event stocks joining the OMXSB, the loading towards the group that the stocks are joining increases, thus supporting the excess comovement hypothesis. However, the loading towards the group that the stocks are leaving see approximately the same increase, which indicates that event stocks do not experience an excess comovement effect of the index event but instead an increase in fundamental beta towards all stocks.

The evidence for a fundamental increase in beta is strengthened by the matched sample approach. When analyzing the differences of coefficients between our original sample and the sample with matching stock based on momentum and size, we find no statistically significant differences. This result is analogous to that of Chen et al (2016) for the S&P 500 and show that when controlling for momentum, or fundamental increases in beta, index events in Sweden show no support for the excess comovement hypothesis.

There are however differences in our results compared to the studies conducted on the U.S. market. First, our results for the sample of stocks leaving the index seem weaker than those of previous studies. We argue that this is a result of the difference in magnitude of fundamental beta changes between winners and losers and the lower concentration of the lowest momentum deciles in our sample compared to the samples of previous studies on the U.S. market. In extension, the lower concentration is possibly a result of the mechanical disqualification process of the OMXSB. In other words, this process will sooner exclude a stock not performing well compared to the time it takes for the S&P 500 index committee to exclude a stock. Even if this seem logical, the matter needs to be investigated further before a conclusion is certain. Second, our differences of coefficients between the pre- and post-event period increases with a Dimson adjustment. This is opposite to the effect seen by the two previous studies, that see a decrease in the difference with approximately one third. Barberis et al (2005) claim that this effect is caused by information diffusion, while Chen et al (2016) suggest that non-synchronous trading or other microstructure effects are plausible. Our results thus support that the effect is not a result of information diffusion but instead of the microstructures of the market concerned.

Finally, we show with a robustness check with increased event window that pre-trading, due to a mechanical qualification process, has no implications on our results that lack support for the excess comovement hypothesis. Instead, the results from this further indicate that event stocks are under a fundamental change of their beta and nothing else.

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