

PASSIVE INVESTING IN THE NORDICS IS MORE PREVALENT THAN YOU THINK

A REASSESSMENT OF PASSIVE INVESTING IN THE NORDICS

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Abstract:

Passive investing has gained significant traction in financial markets globally, yet its true extent remains underappreciated. Inspired by Chinco and Sammon's formative work, "The Passive-Ownership Share Is Double What You Think It Is" (2022), this thesis delves into the Nordic setting, examining the prevalence of passive investment strategies in key Nordic markets. Drawing upon an extensive data analysis, this study aims to shed light on the prevalence of passive investment in the Nordic market by examining trading volume, assets under management tracking these indices, and the time-fixed effects of passive investing. Data sourced from Datastream and Nasdaq provides the empirical foundation for this analysis, which finds significant increases in trading volume on the day before reconstitution, while passive investments directly linked to the indices are still measured to be quite low. We also observe that the increases in trading volume on the day before reconstitution have generally grown larger over time. The findings and discussions of this thesis therein contribute to a deeper understanding of the evolving landscape of passive investing in the Nordics and provide broader implications for methods to study passive investing in financial markets globally.

Keywords:

Passive investing, index reconstitution, index-tracking funds, exchange-traded funds (ETFs), Nordic market

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1. Introduction

Passive investing, which typically is characterized by strategies aimed at mirroring the performance of a market index rather than actively selecting individual securities, has experienced a notable increase in popularity in recent years as a result of increased awareness of the difficulties in consistently outperforming the market (Fama & French, 2010)(French, 2008). Low-cost investment vehicles, such as exchange-traded funds (ETFs) and index funds have democratized access to passive investment strategies by mirroring the composition of popular market indices, such as the S&P 500 or the FTSE 100, at minimal expense ratios (Hill, J., 2016). This cost efficiency is particularly appealing in today's investment landscape, characterized by heightened fee sensitivity and a growing emphasis on achieving competitive investment performance net of fees (Døskeland, Sjuve, & Ørpetveit, 2023).

This demand has been largely driven by empirical evidence, as most famously highlighted by Fama and French (2010) and French (2008), when they brought to light the challenges associated with consistently outperforming the market through active management. The efficient market hypothesis, posited by Fama (1970), suggests that asset prices reflect all available information, making it difficult for investors to consistently exploit mispricing and gain a sustainable edge over the broader market. Consequently, retail and institutional investors alike, have recognized the limitations of traditional active management approaches in delivering superior risk-adjusted returns over the long term (Chinco & Sammon, 2022), underlining the importance of understanding the implications that a rise in passive investments might have on the market and economy at large. This has been explored extensively by scholars like Wurgler (2011) finding that stocks being added to, or dropped from, an index experience significant price changes. Similarly, Sushko and Turner (2018) found that passive investing can contribute to weaker market discipline, and Haddad, Huebner, and Loualiche (2021) discovered that the rise in passive investing has made the demand for individual stocks 11% more inelastic. Despite this attention, the U.S. remains the only market to have its level of passive investment reevaluated in a dedicated study, with Chinco and Sammon (2022) discovering that passive investment in the U.S., beyond index funds and ETFs, is much more prevalent than previously thought.

Off the back of this framework, the primary research question asked in this study is: “What is the prevalence of passive investing in the Nordics?”. Through this question, we aim to measure the extent which passive investing permeates the Nordic stock markets, beyond index funds and ETFs. Specifically, this thesis focuses on examining passive investing in Denmark, Finland, Sweden, and the Baltics, while also indirectly including parts of the Iceland and Norway. These markets collectively represent a holistic representation of the economic structures, regulatory environments, and investor behaviors that are associated with the Nordic’s premier financial markets. By employing a similar methodology as Chinco and Sammon (2022), we aim to quantify whether there is an increase in excess trading volume on the day of, and the day before, reconstitution of our observed indices. Next, we use this excess trading volume to imply a level of assets under management (AUM), that can be deduced to track our observed indices. Lastly, we also observe whether the excess trading volume on reconstitution day has changed over time, through a time-fixed effects study.

The results of these studies show us that there is an increase in trading volume on the the day before reconstitution, though Nordic indices remain small enough in terms of their number of components that passive investments specifically tracking those indices only represent a small amount of the ownership in the respective constituents’ market capitalization, while the amount of excess trading volume, on the day before reconstitution, has typically increased over time in the Nordics.

Through this study, the aim is to challenge prevailing perceptions on passive investing and shed light on the broader implications of the current mix of passive and active investing in the markets, adding further to the findings of Wurgler, Sushko and Turner, and Haddad et. al., and to contribute to a deeper understanding of the evolving landscape that is the Nordic financial markets, providing insights of practical relevance to investors, policymakers, and market participants alike.

2. Literature review and research explanation

2.1. Introduction to passive investing

Active management used to dominate investment strategies, with fund managers employing various tactics to outperform market benchmarks. However, since the emergence of passive investing, which can be traced back to the work of John Bogle, founder of Vanguard Group, who introduced the first index fund for individual investors in 1976 (Bogle, 2007), passive investing has undergone an evolution that has reshaped the landscape of financial markets worldwide. Ever since, passive investment vehicles, including index funds and ETFs have experienced exponential growth, garnering substantial assets under management globally (Carosa, 2024). This evolution has been fueled by a growing body of empirical evidence highlighting the difficulties with aiming to consistently outperform the market through active management (Fama & French, 2010)(French, 2008). As a result, passive investing has become increasingly mainstream, appealing to investors seeking low-cost, diversified exposure to broad market indices.

2.2. The rise of passive investment strategies

There are many reasons for the rise of passive investing, with multiple frameworks being able to clarify its appeal and effectiveness. The Efficient Market Hypothesis (EMH), proposed by Eugene Fama in the 1960s, suggests that asset prices reflect all available information, rendering it difficult for investors to consistently outperform the market through active management (Fama, 1970). In line with this EMH, passive investing aims to replicate market indices and rely on the growth of the general market rather than attempt to exploit mispricing.

Passive investing also focuses on maximizing the benefits of diversification and heeds the importance of minimizing costs, which aligns with the modern portfolio theory (MPT), pioneered by Harry Markowitz (Markowitz, 1952). Thus, by providing investors with diversified exposure to broad market indices at minimal cost, passive investment vehicles (such as index funds and ETF) are constructed to embody these principles of efficient and effective asset management proposed by the EMH and MPT.

2.3. Comprehensive outline of relevant literature

Collectively, all the subsequently presented literature offer a broad understanding of passive investment trends and market dynamics, while providing implications for investor behavior and firm performance. Most importantly, we believe that investigating hidden passive investment in the context of the Nordic markets necessitates a comprehensive examination of previous studies to provide a nuanced perspective on the subject through discussing market structures, investor preferences, and contrary findings to each other, which this collection of literature aims to provide.

2.3.1. The passive-ownership share is double what you think it is
Passive investing has garnered increasing attention in the financial research space as of recent years, particularly with Chinco and Sammon's study, "The Passive-Ownership Share Is Double What You Think It Is", challenging conventional perceptions and becoming a flagship study in the field.

It explores the passive-ownership shares in the U.S. market by examining how much equity is tracking major U.S. indices and measuring the trading volume on days those major indices reconstituted its holdings. By contrasting those numbers with the trading volumes on the days preceding and following the reconstitution, Chinco and Sammon isolate the impact of index reconstitution events and find that the volumes related to reconstitutions are significantly higher than previously believed, indicating a total passive ownership level in the market of 33.5% compared to the 16% that index funds reportedly held in US stock market in 2021. Their study offers an exploration of passive ownership which, to the best of our knowledge, is at present the only major study examining this topic in depth, while challenging conventional perceptions and revealing the true extent of landscape of passive investment landscape. As such, their framework is extensively used for the structure of this thesis and is described in detail in section 3.3.2 "Structure of empirical and statistical analysis".

Chinco and Sammon's study not only underscored the growing preference for passive investing but also highlighted the need for a reassessment of the assumptions and narratives surrounding how passive investment is defined and measured. Importantly, the implication that Chinco and Sammon's findings could extend beyond the U.S. market, calling for examination of the global financial landscape and inspiring

this thesis to investigate the levels of hidden passive investing in the Nordics (Chinco & Sammon, 2023).

2.3.2. The disappearing index effect

Greenwood and Sammon's study, "The Disappearing Index Effect," provides insights into the ever-changing market dynamics and the diminishing impact of indices' reconstitution events over time. Their study documents how, as index tracking grew in popularity, it led to an increase in mispricings associated with index rebalancing and reconstitution events. This, in turn, created trading opportunities for market participants. However, over time, Greenwood and Sammon argue that the market adapted to these dynamics and began to better anticipate index changes, neutralizing their price impact. One of the key findings of the study is the consistent pattern of index rebalancing events' diminishing impact on asset prices over time. In documenting this decline and identifying underlying drivers, Greenwood and Sammon provide this thesis with a valuable perspective on how our findings regarding hidden passive investment impacts market efficiency and investor behavior in the context of pricing. Other noteworthy studies that reiterate these findings and contribute to the legitimacy of Greenwood and Sammon's conclusions are Shleifer (1986), Harris & Gurel (1986), and Chang, Hong and Liskovich et.al (2014).

2.3.3. On the economic consequences of index-linked investing

The economic implications of indexes and index-linked investing is another area of importance for this thesis. The paper "On the Economic Consequences of Index-Linked Investing" by Jeffrey Wurgler (2011) offers a thorough examination of the growth in popularity that market indices have had, their central role in investment strategies, and the impact that they have on stock prices when including or excluding a stock.

A key focus of the study is the effect of index inclusion on stock prices, as Wurgler explains how stocks added to indices tend to experience significant price increases, while those removed witness corresponding drops. Importantly, what Wurgler is describing is not necessarily the same subject as this thesis' focus point. A relevant distinction to make is that Wurgler discusses the pricing impact that a large amount of equity has on the stock when being sold or bought, whereas we solely focus

on measuring the amount of passively invested equity that is causing the abnormal movements regarding trading volume rather than price. Our methodology is further explained below, in section 3.4.2. “Structure of empirical and statistical analysis”.

Ultimately, Wurgler, in contrast to Greenwood and Sammon, finds that the economic consequences of index-linked investing are noticable. His study underlines how mispricings resulting from index-linked investing can have real economic outcomes and complicate investor evaluations. Wurgler’s findings provide this thesis with an excellent starting point for discussing the impact that the hidden amount of passive investment has on the health of the Nordic markets and inspires further research into the topic.

2.3.4. Private equity performance and liquidity risk

Franzoni, Nowak, and Phalippou's delve into a different asset class, in that of private equity, with their paper "Private Equity Performance and Liquidity Risk" (2012). While they investigate the performance of private equity investments and the liquidity risk that is associated with them, their findings regarding the complexities of evaluating investment performance and liquidity risk still manages to provide relevant takeaways that help explain investors’ increasing preference to passively invest. Particularly, their findings regarding liquidity risk's influence on risk management practices may help explain investors' preference for passive strategies.

As investors aim to balance the potential for higher returns with the need for liquidity to meet short-term funding requirements or unexpected cash needs and struggle to employ satisfactory diversification strategies, one implication is that liquidity risk concerns influence overall risk management practices, even beyond private equity. This is especially during periods of market stress, where many prefer highly liquid investments such as index-tracking ones. As such, in the context of providing a framework to understand the underlying market conditions that drive investment, the idea of investors choosing to supplement their portfolios with passive index investments could partly explain the amount of hidden passive investment in the Nordics.

2.3.5. Passive investors, not passive owners

"Passive investors, not passive owners" by Appel, Gormley, and Keim (2016) sheds light on the role of passive institutional investors in corporate governance dynamics. Their study challenges the notion that passive investors are mere bystanders and suggests that they can have significant influence on a firm's governance decisions, subsequently impacting performance. They find that passive mutual funds do influence firms' governance choices, leading to observable changes in governance structures and policies, where firms with a high passive ownership exhibit greater board independence, a reduced presence of takeover defenses, and a higher prevalence of equal voting rights.

This perspective provides nuance the broader implications of hidden passive investment and provides an alternative opinion to the more conventional idea that passive investors merely track market indices without contribute to corporate governance, negatively influencing value creation. Nevertheless, it is also important to note that Appel, Gormley, and Keim's paper has received notable backlash, with many scholars opposing their findings and method. One example is the paper "Selection Bias or Treatment Effect? A Re-Examination of Russell 1000/2000 Index Reconstitution" by Wei and Young (2024), who argue that the methodology used reflects a selection bias instead of a treatment effect. Through additional tests with an adjusted approach, they find contrasting evidence to Appel, Gormley, and Keim.

2.3.6. The implications of passive investing for securities markets

Sushko and Turner's paper "The Implications of Passive Investing for Securities Markets" (2018), provides another important counterargument to the study by Appel, Gormley, and Keim. By examining how the growing popularity of passive investing is replacing active investment styles and investigating how this affects pricings and dynamics in the market, they find that passive investing can contribute to weaker market discipline.

Sushko and Turner argue that the portfolio-wide trading of passive funds can contribute to higher correlation across individual security prices, while also limiting investors' abilities to express disagreement with individual issuers' decisions. They also examine the straightforward implications of passive investing on security pricing, noting that passive fund managers' focus on systematic factors, rather than security-

specific information, may reduce the efficiency of price formation and lead to misallocation of capital, while the mechanical trading patterns of passive funds is argued to influence security prices and contribute to co-movement among index constituents. Furthermore, they also argue that the growth of passive bond funds might encourage an increase in leverage by borrowers, thus impacting financial stability. Their argument is founded in the existence of bond indices, which mechanically replicate the weights of the indices in their portfolios and can create demand for the debt of the larger, higher leveraged, issuers. Supporting this claim, they present an analysis that shows how passive bond funds tend to have a greater exposure to company leverage than to company size.

With their findings of passive investing's dangers, Sushko and Turner's study provides useful insight into the potential implications and consequences of our thesis' findings regarding hidden passive investment and further illustrates the importance of better measuring the level of passive investing in the Nordic market.

2.3.7. How competitive is the stock market? Theory, evidence from portfolios, and implications for the rise of passive investing

The paper "How Competitive is the Stock Market? Theory, evidence from portfolios, and implications for the rise of passive investing" by Haddad, Valentin, Huebner, Paul, and Loualiche, Erik (2021) delves into the dynamics of investor competition and its implications, most interestingly for this thesis, in the context of the rise of passive investing. Traditionally, theory posits that financial markets are fiercely competitive, implying that changes in investor behavior have minimal impact on prices due to the immediate adjustments from other investors. However, their study challenges this notion by estimating a demand system with flexible strategic responses among institutional investors in the U.S. stock market.

The authors' findings suggest that when an investor is surrounded by less aggressive traders, she trades more aggressively, though this response is a lot weaker than what is typically anticipated by classic hypotheses on the subject. They find that strategic responses only compensate for two thirds of the effect of changes in investor behavior on the aggregate demand for a stock, which implies that the rise in passive investing leads to more inelastic markets. Specifically, they measure that the rise in passive investing over the last two decades has made the demand for individual stocks

11% more inelastic, indicating that the stock market is not as fiercely competitive as commonly believed. Another biproduct of this paper is that they also estimate the level of passive investing, which they quantify to highly similar levels as Chinco and Sammon do in their previously mentioned paper "The Passive-Ownership Share Is Double What You Think It Is" (2023).

These findings are hugely important for our study, especially in our discussion regarding the implications of the level of passive investing and what a larger amount of passive investing means for the market. By underscoring the importance of how investors compete in financial markets, Haddad, Valentin, Huebner, and Loualiche's paper provides valuable insights and another starting point for the discussion of our findings in this thesis.

2.4. Research clarification

Given the demonstrated findings of the presented literature, especially the findings in "The Passive-Ownership Share Is Double What You Think It Is" (Chinco & Sammon, 2022), "On the Economic Consequences of Index-Linked Investing" (Wurgler 2011) and "How competitive is the stock market? Theory, evidence from portfolios, and implications for the rise of passive investing" (Haddad, Valentin, Huebner & Loualiche, 2021), the following research question is proposed for this thesis' subject:

- "What is the prevalence of passive investing in the Nordic market?"

Through this question, we aim to investigate the behavior of passive investors in the Nordics and explore how much passive-like investment there is in our main markets of observation. These have been limited to primarily Denmark, Finland, Sweden, and the Baltics due to their prominent indices and well-known stock markets, though the remaining Nordic countries Iceland and Norway are indirectly included through broad Nordic-focused indices. By measuring the passive investments tracking the major indices in these markets and investigating the reconstitution dates of the indices, we hypothesize that there will be a significant increase in trading volume of the affected stocks on the day before and the day of the indices' reconstitution, akin to non-index fund investors shadowing the index constituents and, thus, indirectly making passive investments a larger equity share of the market.

The basis of this logic rests on the argument that if there is significant equity in the market that is allotted to follow the index's constituents and, therefore trades like that of an index-tracking fund, then, it is effectively acting in a passive manner and should have the same implications on corporate investment decisions, financing, and investor strategies as the passive investing found in the previously mentioned "On the Economic Consequences of Index-Linked Investing" (Wurgler, 2011) and "The Passive-Ownership Share Is Double What You Think It Is" (Chinco & Sammon, 2022). Thus, our aim is to challenge prevailing perceptions on passive investing and explore the broader implications of the actual level of passive versus active investing in the markets. In our effort to do so, the hope is to also create value for index-related studies through our data collection, where we have both compiled and combined data on index reconstitution days, index weightings, index market values and securities' pricing and trading volume data. Hopefully, the insights from collecting these datasets will aid and inspire future scholars to further analyze the subject of index investing.

3. Data and empirical design

In the following section, the process of the data collection for this thesis is explained in detail, including what type of data was used for our analysis, the descriptives of that data, which indices were observed, and the source from which that information was collected. This section also explores the empirical design of this thesis' topic of study, clarifying the methodology used and describing the empirical design that was employed.

3.1. Index descriptives

As the objective of this thesis is to measure the hidden passive investing in the Nordics, which we identify as the most prominent indices in Denmark, Finland, and Sweden, accompanied by indices that cover the largest companies in all of the Nordics (including both Iceland and Norway whose absence, in regard to having their own country-specific indices excluded from the study, is discussed in section 3.2. "Methodology of data collection"), as well as the Baltics, the main data needed pertained to the following indices of this study:

Table 1. Index information

Ticker	Area	Components	Currency	Reconstitutions	Weight
OMXB10	Baltics	10	EUR	January/July	Market Cap
OMXC20	Denmark	20	DKK	June/December	Market Cap
OMXH25	Finland	25	EUR	February/August	Market Cap
OMXN40	Nordics	40	EUR	June/December	Market Cap
OMXNLCEURGI	Nordics	233	EUR	December	Market Cap
OMXS30	Sweden	30	SEK	January/July	Market Cap

Note: All information about the indices was collected from Nasdaq's own website (Nasdaq, 2024, accessed on 04/18/2024 to 04/22/2024). OMXNLCEURGI does not have a cap on its number of components, though 233 reflects the most recent amount at the time of the data collection.

To better understand the underlying data, a thorough description of the indices is required. Our focus is on Nasdaq's Nordic indices, which happen to be the OMX-segmented indices. These are designed to measure the performance of the securities in each of the relevant markets based on market capitalization or market price. As such, all observed indices are weighted against the market and, thus, the size of each constituent is determined by the size or price of the stocks themselves.

The OMXB10 is an index focusing on the 10 largest companies in the Baltics and chooses constituents semi-annually, using data from the end of November for its January reconstitution and data from the end of May for its June reconstitution, with its reconstitution days being announced at least five days in advance. The changes become effective at market open on the day of the reconstitution, with the top 10 securities from the Nasdaq Vilnius, Nasdaq Riga, and the Nasdaq Tallin stock exchanges being selected for inclusion during each reconstitution (Nasdaq, 2024).

The OMXC20 is the most prominent index in Denmark, representing the Nasdaq Copenhagen stock exchange and includes the 20 largest and most traded securities on Nasdaq's Danish stock exchange. The index is reconstituted twice per year, in June and December, though it should be noted that the June date uses data from the end of May and the December date uses data from the end of November, while that the changes themselves become effective immediately on market opening on the date of the reconstitution (the fourth Monday every June and December). Notably, the changes are also announced a minimum of five days prior to the reconstitution (Nasdaq, 2024).

The OMXH25 index selects its constituents semi-annually, in February and August, using data from the end of December for its February reconstitution and data from the end of June for its August reconstitution. Its reconstitution days are announced five days in advance and become effective at market open on the day of the reconstitution, with the top 25 securities on the Nasdaq Helsinki stock market being selected for inclusion during each reconstitution (Nasdaq, 2024).

The OMXN40 is one of the most prominent large Nordic indices, with a broad collection of the 40 largest and most traded stocks listed on the Nasdaq Copenhagen, Nasdaq Helsinki, Nasdaq Iceland, and Nasdaq Stockholm stock exchanges. Thus, there is an overlap in a part of the composition of the OMXN40 and the represented indices from Denmark, Finland, and Stockholm in this study, however, as they operate independently and mostly reconstitute on slightly different days, there does not seem to exist a relevant overlap in reconstitution days of the same stock on the same date, thus not compromising the effectiveness of our analysis. The OMXN40 reconstitutes semi-annually, in June and December, with alterations being effective on market opening and announced at the latest five days prior, in line with the standard process for Nasdaq indices (Nasdaq, 2024).

The OMXNLCEURGI is, similar to the OMXN40, a large and broad index that focuses on the entire Nordic segment of Nasdaq's stock exchanges OMXC, OMXH, OMXI, OMXN, and OMXS. It also focuses on Nasdaq's Large Cap segments, excluding securities of its Medium Cap, and Small Cap size. These categories are defined by Nasdaq as the following:

- Large Cap securities have a market capitalization of over €1 billion.
- Middle Cap securities have a market capitalization of between €150 million and €1 billion.
- Small Cap securities have a market capitalization of less than €150 million.

This results in the index being notably larger than any other in our dataset, with 233 components. Unlike the other five observed indices, the OMXNLCEURGI does not announce its specific reconstitution changes in advance, though it is still public information that the index reconstitutes annually in December with its changes becoming effective immediately on the first trading day of January (Nasdaq, 2024). The same argument as with OMXN40, regarding the somewhat overlapping holdings yet holds for OMXNLCEURGI as well.

Lastly, the OMXS30 is the main index available on the Swedish stock market and in Nasdaq's Swedish lineup of indices. It contains the 30 most prominent and actively traded stocks on the Nasdaq Stockholm stock exchange and reconstitutes in January and July, using respective data from the end of November and the end of May. The OMXS30 follows the typical Nasdaq process of publicly announcing its changes at a minimum of five days prior to the reconstitution day, putting the revisions into effect at market open on the first days of January and July each year (Nasdaq, 2024).

3.2. Descriptive data

In the table below, we present the descriptive statistics of our collected index data, both their total amount of reconstitutions, i.e. observations, but also how many of those reconstitutions had available weight data at the time of the trade. It also goes in depth over how many observations are set on the reconstitution day "t", versus the day before "t-1", as well as describes the intricacies of the data regarding the split of joiners and leavers of the indices.

Table 2. Sequentially filtered data of observations

Data on the indices				
	Total number of observations	Observations with reconstitution dates	Observations with volume data	Observations with weight data
OMXB10	84	74	72	0
Joiners Leavers	39 45	34 40	33 39	0 0
OMXC20	158	120	98	58
Joiners Leavers	82 76	56 64	48 50	27 31
OMXH25	195	172	111	34
Joiners Leavers	106 89	100 72	56 55	19 15
OMXN40	169	114	104	84
Joiners Leavers	96 73	53 61	48 56	40 44
OMXNLCEURGI	443	165	163	153
Joiners Leavers	317 126	111 54	109 54	109 44
OMXS30	115	60	41	17
Joiners Leavers	72 43	37 23	22 19	10 7
Summary	1164	705	589	346
	712 452	391 314	316 273	205 141

Note: All information about the indices' reconstitutions was collected through Eikon and Datastream, while information on index weights was collected from Nasdaq's own website, through a login provided by Nasdaq (Nasdaq, 2024, accessed on 04/18/2024 to 04/22/2024).

As illustrated in table 2 “Descriptive data of observations “, we obtained a large dataset with a total of 1164 observations, which we characterize as any individual reconstitution made by an index, regardless of the timing of it. These observations can include multiple reconstitutions of the same security, just at different points in time, which means that the key distinction for each observation is that they are unique reconstitutions, despite the same security often showing up multiple times in our datasets as a joiner at first and then a leaver at a later point. This pattern occasionally occurs multiple times, with a security being added and dropped from an index more than once. In the row below each index, the observations are further split up into whether they were joining or leaving an index.

Next, the observations are filtered to only include the joiners and leavers that occur on the indices' normal, regularly scheduled, reconstitution days (as presented in section 3.1 “Index descriptives”). Some securities join or leave the indices outside of these regular reconstitutions, which is often a sign of something irregular occurring around the stock in question, such as the company declaring for bankruptcy or being acquired and taken off the market. As such, these events do not adequately represent a normal reconstitution and were filtered out. Next in the table, the observations are also

filtered on if we were able to obtain volume data for the security in question, giving us access to the traded volume of the security on the reconstitution day (t), the day before ($t-1$), as well as the 15 trading days before and the 10 trading days after the reconstitution date. This is needed in order to measure the level of trading each stock is experiencing on the reconstitution day.

Finally, the observations are also filtered based on whether the indices had available weight data at each individual reconstitution date or not, leaving out the observations lacking individual index-weight data. This is only relevant for the second portion of our analysis, which aims to measure the level of passive ownership in the Nordics, while our first segment that aims to determine whether there is an increase around the reconstitution day only needs data on the securities' individual trading volume, not the indices' weight data. Nevertheless, we observe that there often is a significant drop-off in available data for the index-weights, with the Baltic index OMXB10 not having any available data at all and, as such, was not able to partake in the second portion of our study. As the different sections, in practice, are completely detached from each other and functionally are two different studies that we intertwine to get more nuanced findings, this does not create any issues in terms of the structure, rationale or relevancy of our findings.

3.3. Methodology of data collection

In establishing our methodology, it was important to define the scope of the study and, given the lack of research on this topic in the Nordics, it was deemed an ideal geographical restriction. Furthermore, as this study aims to measure the level of passive investment, an important determinator for which indices were viable to study was whether they had readily available data regarding its reconstitutions, as well as weightings at the time of each reconstitution. For this purpose, Nasdaq's indices were an ideal fit. Not only was the data of the indices' constitutions readily available through the datahubs of SSE's access to Eikon (Datastream, 2024, accessed 03/20/2024), both in terms of which securities were added or removed and the exact date of each constitution, but through Eikon and Datastream, we were also able to obtain datasets containing the trading volume of each reconstituted security as well. With this, the only other main data that was needed was the exact weightings of each index at each

reconstitution day, as well as the market capitalization of the index constituents around the day of each reconstitution. Through cooperation with Nasdaq's index services, we were graciously given access to their catalogue of index data and were able to retrieve the weightings and market capitalization data straight from Nasdaq's own database (Nasdaq Indice Services, 2024, accessed 04/20/2024).

An important point to discuss regarding the data collection is the decision to exclude both Iceland and Norway's own indices OMXI15 and OMXO20GI from our dataset. Ultimately, while we would have preferred to include these countries in the study, given the lack of data in Datastream, Iceland or Norway were not viable inclusions to our study. Another limitation in our data collection stems from the lack of index weight data for OMXB10. As mentioned in section 3.2 "Data descriptives", as we were able to obtain data on its reconstitutions and volume data on the securities involved, while we could still use the index for the purpose of measuring the spikes in volume around the reconstitution dates, were forced to exclude it from the quantification of the passive investment in the Nordics.

Meanwhile, it should also be discussed as for why the OMXB10 index was included. Though the Baltics are not officially a part of the Nordics, as a region, they do have a close relationship with the Nordic countries, especially regarding trade and business. Furthermore, the countries are fairly regularly paired together in analytical and regional data, which indeed is how Nasdaq itself treats the Baltics, by pairing it up with the Nordics in its index categorization. As such, it felt apt to include the Baltics in our dataset for the purpose of gaining more interesting and relevant datapoints and to allow us the opportunity to gain insights from a region which is often considered tangent to the Nordics. Through the restrictions and additions mentioned in this section, the guidelines and limitations for this study's datasets were set up, for which all the necessary data mentioned in section 3.1 and 3.2 was methodically collected.

3.3.1. Methodology of data cleaning and handling

Having established our method for data collection, an equally important segment was how we handled the cleaning and organization of the data, which was not only greatly time consuming, but also an integral part in enabling our analysis. After retrieving the reconstitution data for each index, the next step was to collect the daily turnover volume

for each observation in that dataset 30 calendar days before and 20 calendar days after each reconstitution date. Given the nature of this retrieved data, it included multiple instances of missing observations, with “NA” (Not Available) data during holidays and other non-trading days when the markets were closed. By cleaning this data further, we retrieved the 15 consecutively available trading days before, and the 10 consecutive available trading days after each reconstitution date, which we then structured in rows from t_{-15} to t_{+10} for each observation. Following this, the observations were also filtered on if whether occurred on the annual and semi-annual reconstitution, or outside of normal reconstitution dates, following our logic from section 3.2. Those that were on regular reconstitution dates were then included in the final concatenated dataset that was used in the analysis of this thesis.

Additionally, some individual stocks had instances where they lacked sufficient levels of volume data, which then also had to be excluded from the final dataset as there was no way to accurately retrieve data comparable to the setup of the rest of our data. These cases with insufficient data often contained consecutive NAs in the days leading up to, or following, the reconstitution and mostly occurred outside of the annual or semi-annual reconstitutions. A significant amount of the time, these instances of missing stock data were due to the stock in question having a unique circumstance around it. An example of this was the inclusion of Essity on the 12th of June of 2017, a spin-off of the company SCA, which was already included in the OMXS30 since 1996 (Karlsson and Stoltz, 2017). Lastly, some values were removed due to errors in index reconstitution reports (in some instances, indices were reported to add and remove the same stock on the same day or on consecutive days).

Having finished the cleaning and structuring of the trading volume data, the next step was to do the same for the constituents’ weights as well. This data was manually collected from Nasdaq’s online database and inserted into the dataset, in line with what was explained in section 3.3. above. To obtain the correct data, it was important to properly identify the correct date for joiners and leavers, respectively. For stocks that were included on reconstitution, we observed the date denoted as “ t ”, as those were the dates where weight data was first available for each joiner, while for excluded stocks, we instead chose the date “ t_{-1} ”, which represents the final day that the stock was included in the index. Occasionally, there would be a discrepancy in the dates

retrieved from Datastream and the dates where weight data was available in Nasdaq's database. In those instances, dates were adjusted to align with what was reported by Nasdaq, the index provider itself. The weight-data was available for most indices starting in 2009, which by construction limited the dataset used to calculate AUM and excess AUM to begin with this year, rather than with the oldest year from the original trading volume dataset.

Data related to our estimates of the AUM and excess AUM that tracks each index was retrieved via Datastream in a similar manner to the volume data. A long-run of turnover volume measured in number of shares from t_{-182} to t_{-2} was gathered as a measure of the average trading volume when calculating the excess AUM. Simultaneously, the value weighted average price (VWAP) at t and t_{-1} was collected and used to estimate both the AUM and excess AUM. In some instances, there was no available price data, which resulted in that specific observation being disregarded. Lastly, we also obtained data from Nasdaq on the daily market cap of the indices' constituents, from an interval of our oldest observation to the most recently available data. These were matched at t and t_{-1} for each observation in each index, creating the structure for the excess AUM computations in relation to the market cap.

3.4. Empirical design

In the following section, our aim is to provide clarity into the terminology specific to our study, explaining different choices of definitions and groupings of datasets and data classes. This section also explores the empirical method and structure of the statistical analysis conducted in this thesis in depth, with the aim of making it more comprehensible for the reader and allowing for a greater understanding of this thesis' empirical measures and processes.

3.4.1. Clarification of terminologies

In the context of the empirical design of this study, it is important to clarify what we identify as passive trading. To do that, we first establish the term "Passive-like trading", which we summarize as any trade done on the reconstitution day or the day before, concerning the same stock as the one being reconstituted in the relevant index. This gives us the basis of the data for our investigation, and the total trading volume of each

relevant stock on the observed days. This builds off the framework and findings in Chinco and Sammon's study, "The Passive-Ownership Share Is Double What You Think It Is" (2023), mentioned in 2.1.3 of the "Comprehensive outline of relevant literature" section of this paper. Specifically, their notion that there is a uniform behavior among passive investors upon a reconstitution. The methodology employed in their study categorizes any portfolio adjustments made during the closing hours of the market on reconstitution day as passive investments, irrespective of investor profile.

In our study, we extend this statement to cover the entire reconstitution day and the day prior to the reconstitution day. This is done to adjust for Nasdaq's indices, with the exception of the OMXNLCEURGI, all announcing what reconstitutions will be made way in advance and commencing the trades in the beginning of each reconstitution day rather than the end, which gives investors the chance to both act on the information beforehand, such as a day prior to the reconstitution, as well as trail the reconstitution trades before market close on the day of reconstitution. By extending our window of observation to the day prior and the entire reconstitution day, we hypothesize that we can capture these traders and closet indexers in our analysis who might not align their trades exactly with the reconstitution date depending on if they want to lead or trail the reconstitution.

Just as Chinco and Sammon (2022) suggest regarding their own methodology, this approach consequently means that our data will capture investments made by individuals who may not identify themselves as passive. The example brought up by is a scenario where an active fund manager oversees \$250 billion in assets under management (AUM), with 20% of this sum passively tracking the Russell 1000 index (an index included in their study). If, on the reconstitution day a manager purchases 103,000 shares of Yeti Inc. (a stock in the Russell 1000) at \$92.07 per share, this would amount to \$50 billion at market close, and this \$50 billion would be categorized as AUM linked to the Russell 1000. They argue that, while it is plausible that certain active investors strategically delay their trades to capitalize on the heightened trading activity during reconstitution days, they do not find that there is any discernible decrease in trading volume in the days leading up to the reconstitution and following inclusion or exclusion of securities from an index, suggesting that these traders are not just active investors who happen to be trading at market close.

Additionally, they highlight that reconstitution events inherently involve modifications to at least two securities (with one being added to an index and one being dropped to keep the index at its intended number of components). Thus, the variability in trading volume on reconstitution days (and in our case with Nasdaq's approach and policy regarding the release of the information and the timing of reconstitutions, also the day before reconstitution) as compared to trading volume during the days before can confidently be argued to be almost completely explained by passive investor demand. As such, deriving from Chinco and Sammon's arguments and findings, we posit that any trading volume on the reconstitution day, that is in excess of the average trading volume during the days leading up to the reconstitution day, can confidently be categorized as passive investment.

3.4.2. Structure of empirical and statistical analysis

To explain the structure of our empirical methods, we first establish the makeup of our research processes and approach. To reiterate our research statement, the aim of this thesis is to quantify the prevalence of passive investing in the Nordic market. To answer this question, we establish a step-by-step approach where we aim to:

1. Measure whether there is a significant increase in trading volume on the day before ($t-1$) and the day of the reconstitution (t) of an index.
2. Determine how much AUM that the trading volume on the day before ($t-1$) and the day of the reconstitution (t) implies are tracking each index.
3. Investigate whether the amount of excess trading volume has increased over time, both during the day before ($t-1$) and the day of the reconstitution (t).

Through these steps, our aim was to establish a holistic approach that covered not only finding out if indices' reconstitutions contribute to higher trading volume of a stock, but also quantifying exactly how much of the market is trading passively, in addition to explicitly passive investors such as index funds. It is also important to reiterate that, with this thesis having the target of studying the Nordic market in a similar way to Chinco & Sammon's (2022) study of the U.S. market, a large part of our approach is inspired by their methods. Having established these goals and guidelines, we can begin to explain the methodology of our empirical analysis in detail.

1. Measuring increase in trading volume

Firstly, we examined whether there is a notable increase in trading volume of stocks that are the subject of the reconstitution of an index. We began by taking the data of the reconstitution days and the reconstituted stocks for each index and matching it with the data of each stocks' trading volume. This provided us with a dataset of each reconstitution and accompanying trading volume leading up to, and during, the reconstitution day, which enabled us to compute the average trading volumes in the period before the reconstitution. We then compared the average trading volume with the specific trading volume on t and $t-1$ by running initial regressions in R.

Running regressions with a broad definition of our volume was not ideal, as it provided us with an analysis of each individual stock, rather than each index at large, which produced too many variables and made the results of each stock incomparable to the others, due to the large difference in numerical trading volume between stocks of different sizes. This also created a large variance in the dataset. As we wanted to group all observations of a single index together and needed to have the trading volumes comparable to do so, we decided to transform our trading volumes into trading ratios instead. To achieve this, we took the trading volume of each security on days t and $t-1$ and divided it with the average trading volume of the same security in the 14 days leading up to the reconstitution for t and the day before the reconstitution for $t-1$. These volume ratios were then used to create a set of regressions, both described below:

(1)

$$Volume Ratio_t = Trading Volume_{t,i} / Average Trading Volume_{t-15:t-2,i}$$

(2)

$$Volume Ratio_{t-1} = Trading Volume_{t-1,i} / Average Trading Volume_{t-15:t-2,i}$$

Note: The intervals always refer to inclusive class intervals.

(3)

$$Volume_i / Average Volume_{t-15:t-2,i} = \beta_0 + \beta_1 \times Recon_{t,i} + \beta_2 \times Joiner_i$$

(4)

$$Volume_i / Average Volume_{t-15:t-2,i} = \beta_0 + \beta_1 \times Recon_{t-1,i} + \beta_2 \times Joiner_i$$

Note: The intervals always refer to inclusive class intervals.

In this equation, “*Recon*” is a dummy variable that refers to each individual reconstitution day, taking the value of 1 if it is a reconstitution day and 0 for any other day. “*Joiner*” is another dummy variable that takes on a value of 0 or 1, with 0 indicating an observation is a leaver of its index and 1 signifying it is a joiner of its index. This allowed us to analyze potential differences between leavers and joiners in our regressions and whether a security was traded on a reconstitution day or not. Notably, we set up two separate regressions, one for the reconstitution day and one for the day before the reconstitution day. This was done following the logic in section 3.4.1. “Clarification of terminologies”, where it was mentioned how, with Nasdaq’s approach and policies regarding the release of information and the timing of reconstitutions, the day before reconstitution is also relevant to observe. Through these regressions, we were able to get results for each of the six indices included in this study, giving us an idea of whether there is an increase in trading volume on the reconstitution date and the day before reconstitution. The results of these regressions are presented in section 4.1.

2. Determining the amount of index-linked AUM

The next step was to conduct the second half our study, aiming to establish how much of the trading volume on the day before and the day of the reconstitution of an index is due to hidden passive investors matching and trading on the indices’ reconstitutions. To do this, inspiration was taken from the methodology of Chinco and Sammon (2022) as previously mentioned. In their study, they set up the following equation which aims to find out the implied amount that is indexed based on the increase in trading volume for each stock:

(5)

$$ReconDay_t Volume \times Price = AUM_{indexed} \times IndexWeight$$

Note: The intervals always refer to inclusive class intervals.

Importantly, this statement assumes that each stock in question is not the subject of reconstitution in another index on the same date that our observed index reconstitutes. Furthermore, given that we have a slightly different limitation in terms of our reconstitution day, where we include the entire day as opposed to Chinco and Sammon’s limit of only trades after 4:00pm, we need to adjust our equation somewhat

to reflect that and filter out regular traders. With this stipulation, we present the following equation for our study:

$$\begin{aligned} & (ReconDay_t Volume - AverageVolume_t) \times Price \\ & = ExcessAUM \times IndexWeight \end{aligned} \tag{6}$$

$$\begin{aligned} & (ReconDay_{t-1} Volume - AverageVolume_t) \times Price \\ & = ExcessAUM \times IndexWeight \end{aligned} \tag{7}$$

Note: The intervals always refer to inclusive class intervals.

In these equations, “*ReconDayVolume*” refers to the total trading volume of each observation on the reconstitution date or the day before and “*AverageVolume*” represents the average level of long-run trading volume from 180 days prior to the reconstitution day and the day before the reconstitution date, respectively. This allowed us to filter out the normal level of trading volume for each stock and establish baseline for what amount is expected to be traded on any certain day, any trading volume in excess of that could be attributed to index investing. Next is “*Price*”, which reflects the volume-weighted average stock price at the corresponding date. “*ExcessAUM*” is our replacement for “*AUMIndexed*”, as it now refers to the implied amount of assets under management (AUM) that would have to be indexed to motivate the level of excess trading volume of each stock at the time of observation, while “*IndexWeight*” is a term representing each observation’s weight in the index at the time of reconstitution, either the weight it was assigned when it joined or the weight it was at when it was dropped.

This “*ExcessAUM*” is then taken for each stock and divided by “*Index Market Cap*”, which represents the market cap of each index’s constituents on the day of observation, which then creates an aggregated ratio for the passive AUM in the market, relative to the size of each index, using the following formula:

$$ExcessAUM_i / Index\ Market\ Cap_i = ExcessAUM_{as\%of\ MarketCap_i} \tag{8}$$

Note: The intervals always refer to inclusive class intervals.

Notably equations 6, 7, and 8 are done on all indices except OMXNLCEURGI, based on our findings from part 1, where we observe each index's increase in trading volume. As to be presented in section 4.1, it did not show any significant results for an increase in trading volume on the reconstitution day or the day before and was therefore excluded from this step. The final output of this equation is the average AUM related to each of our five indices and the measurement which indicates how much actual AUM each index is measured to have tracking it, when using our method that aims to capture even the passive investors that are not explicitly tracking the indices, i.e. the previously invisible or unknown passive investors.

3. Examining how the level of passive investing has changed over time

Having produced a result regarding the actual amount of passive investing in our Nordic indices, the next step was to investigate how the number of passive investors has changed over time, both during the day before ($t-1$) and the day of the reconstitution (t) of an index. For this purpose, regressions testing for time-fixed effects were set up under the following stipulations:

(9)

$$\begin{aligned} \text{Volume}_i / \text{Average Volume}_{t-15:t-2,i} \\ = \beta_0 \times \text{Timeframe}_j + \beta_1 \times (\text{Recon}_{t,i} \times \text{TimeFrame}_j) \\ + \beta_2 \times \text{Joiner}_i \end{aligned}$$

(10)

$$\begin{aligned} \text{Volume}_i / \text{Average Volume}_{t-15:t-2,i} \\ = \beta_0 \times \text{Timeframe}_j + \beta_1 \times (\text{Recon}_{t-1,i} \times \text{TimeFrame}_j) \\ + \beta_2 \times \text{Joiner}_i \end{aligned}$$

Note: The intervals always refer to inclusive class intervals.

Similar to the final versions of the regressions testing for increase in trading volume, these regressions used the volume ratio component, which once again enabled us to exclude the “Security” variable and observe the characteristics of each individual index, rather than each individual stock. The interactive dummy variables “Recon x TimeFrame”, represents whether an observation is on the reconstitution date and if it belongs to one of our time periods, while “Joiner” is a second dummy variable that takes on a value of 0 or 1, where 0 indicated an observation was a leaver of its index and

1 signified it was a joiner of its index. This enabled us to filter our regression for both joiners and leavers and whether a security is traded on a reconstitution day or not. We also include the “Timeframe” variable as a dummy multiplied with β_0 , which serves to absorb variation in volume/average volume over time that is not related to the reconstitution date and the variable “Recon”. As prior, these regressions were set up for both the reconstitution day t and the day before, $t-1$, while also being run for each individual index, providing us with a total of 12 regressions. Lastly, the “ j ” term was introduced for the “TimeFrame” variable, set up as a categorical variable in R, and signified the period in question for each time frame in the following structure:

$$j = \begin{cases} 1 = 2021 - 2024 \\ 2 = 2017 - 2020 \\ 3 = 2013 - 2016 \\ 3 = 2009 - 2012 \\ 5 = 2005 - 2008 \\ 6 = 2001 - 2004 \\ 7 = 1997 - 2000 \end{cases}$$

Note: All values for the given intervals are inclusive, i.e. including the upper and lower limit.

Using this set up, we were able to obtain results for how the level of passive investors tracking our indices’ reconstitutions has changed over the years, which is presented in section 4.3.

Additional studies to complement our findings

Having concluded the three primary segments of our study, we found that our research topic was firmly explored from a broader, macroscopic perspective. To enhance our study’s comprehensiveness and further contextualize our findings, we delve into the specific impact of index investing on two of the companies from our domestic market of Sweden. Thus, we launched a brief case study on Sinch (SINCH.ST) and Securitas (SECUB.ST), which were chosen for a multitude of reasons. Firstly, we needed two stocks that had observations in our dataset sufficiently recently, falling into period 1 from our time-fixed effects study. Secondly, we required one joiner and one leaver, to give us the opportunity to observe both scenarios. Thirdly, we wanted similar observations to the average findings from step 1 and 2 of this study. Sinch and Securitas fulfilled these requirements, with both having been the subject of a reconstitution on the

1st of July in 2021, Sinch being a joiner and Securitas being a leaver of the same index. Furthermore, the fact that these stocks were the only subjects of the reconstitution in July of 2021 meant that they effectively were two sides of the same coin. With Sinch and Securitas as the stocks of choice for our case study, we computed their trading volumes around the reconstitution from $t-15$ to $t+10$ and illustrated the observed changes in volume using bar charts, to better visualize our findings from especially part 1 of our study and to make the information more digestible for readers of this thesis.

A second additional study, added to provide further context to the individual insights from Sinch and Securitas, was the addition of Nibe (NIBEb.ST) to the OMXS30 index on the 2nd of January 2023. Similar to the reconstitution of Sinch and Securitas, this is a relevant datapoint for the understanding of current markets, due to it being such a recent constitution. Furthermore, this specific case has special characteristics that make the reaction on reconstitution day especially interesting. Whereas Sinch and Securitas represent the standard reconstitution case, the public only knew that the OMX30 was one component short of its baseline of 30 companies when Swedish Match was removed. It took until after market close, at 6pm on the 22nd of December, right before the holidays (Augustsson, 2022) for it to be officially announced Nibe was set to be the latest member of the OMXS30. As such, it becomes an interesting case study for how the passive investors measured in study 1, 2, and 3 react with such a short notice. Similar to our method regarding Sinch and Securitas, we calculated Nibe's trading volumes around the reconstitution, from $t-15$ to $t+10$, and presented the observed changes in volume using bar charts, to illustrate our findings and contrast them to our findings from observing Sinch and Securitas.

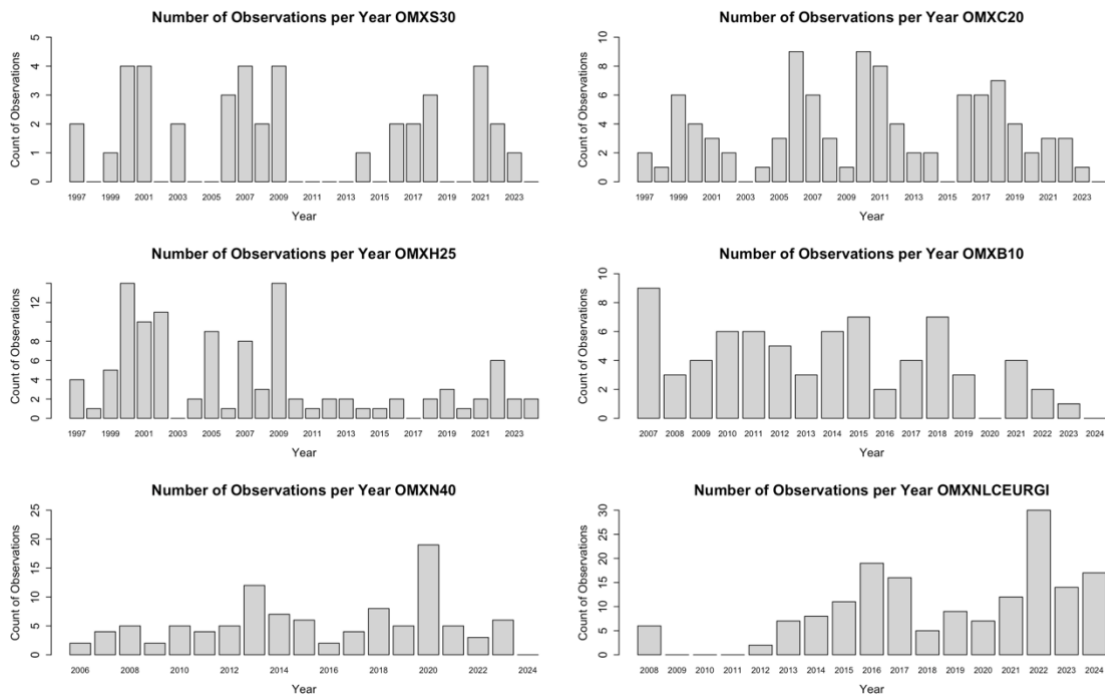
4. Descriptive statistics

In the following section, we present the empirical findings of this thesis' four analyses as they were illustrated in section 3.4.2. "Structure of empirical and statistical analysis". We show the results of each of the four sections of our study, displaying tables for our regressions and graphs to illustrate our findings, while explaining the results in detail.

4.1. The increase in trading volume on reconstitutions

In the following section, we provide descriptive data for the trading volume numbers and present the regression outputs of equations 3 and 4, showing the results of step 1 from section 3.4.2., to measure whether there is a significant increase in trading volume on the day before (t-1) and the day of the reconstitution (t).

Figure 1. Observations per year for each index



Note: The number of observations on the y-axis displays actual numbers, i.e. there were two stocks being reconstituted in 1997 for OMXS30.

In Figure 1 above, we illustrate the spread of the number of observations we were able to collect regarding observations per index. The y-axis illustrates the number of

observations and the x-axis the years of available data, where every other year is labelled. Any empty years indicate that there were no reconstitutions that year, such as in 1998 for OMXS30.

Table 3. Regression output: day of reconstitution

	<i>Dependent variable:</i>					
	C20 Vo/ Avg _{t-15:t-2} (1)	S30 Vo/ Avg _{t-15:t-2} (2)	H25 Vo/ Avg _{t-15:t-2} (3)	B10 Vo/ Avg _{t-15:t-2} (4)	N40 Vo/ Avg _{t-15:t-2} (5)	NLCEURGI Vo/ Avg _{t-15:t-2} (6)
Recon t	0.013 (0.080)					
Joiner	0.047 (0.031)					
Recon t		0.153 (0.194)				
Joiner		0.131* (0.075)				
Recon t			0.251 (0.191)			
Joiner			0.109 (0.073)			
Recon t				0.248 (0.174)		
Joiner				0.126* (0.067)		
Recon t					-0.107** (0.053)	
Joiner					-0.035* (0.021)	
Recon t						-0.298 (0.321)
Joiner						0.225* (0.131)
Constant	0.978*** (0.022)	1.062*** (0.055)	1.240*** (0.053)	0.911*** (0.046)	0.937*** (0.014)	1.025*** (0.108)
Observations	2,548	1,066	2,886	1,872	2,704	4,238
R ²	0.001	0.003	0.001	0.003	0.003	0.001

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 4. Regression output: day before reconstitution

	<i>Dependent variable:</i>					
	C20 Vo/ Avg _{t-15:t-2} (1)	S30 Vo/ Avg _{t-15:t-2} (2)	H25 Vo/ Avg _{t-15:t-2} (3)	B10 Vo/ Avg _{t-15:t-2} (4)	N40 Vo/ Avg _{t-15:t-2} (5)	NLCEURGI Vo/ Avg _{t-15:t-2} (6)
Recon t-1	0.373*** (0.079)					
Joiner	0.047 (0.030)					
Recon t-1		1.794*** (0.187)				
Joiner		0.131* (0.072)				
Recon t-1			1.857*** (0.188)			
Joiner			0.109 (0.072)			
Recon t-1				0.779*** (0.174)		
Joiner				0.126* (0.067)		
Recon t-1					0.161*** (0.053)	
Joiner					-0.035* (0.021)	
Recon t-1						-0.384 (0.321)
Joiner						0.225* (0.131)
Constant	0.964*** (0.022)	0.999*** (0.053)	1.178*** (0.052)	0.890*** (0.046)	0.927*** (0.014)	1.028*** (0.108)
Observations	2,548	1,066	2,886	1,872	2,704	4,238
R ²	0.010	0.083	0.034	0.013	0.004	0.001

Note:

*p<0.1; **p<0.05; ***p<0.01

In table 3 and 4, the regressions are presented for each index, here shortened to their names without the “OMX” tag (i.e. S30 instead of OMXS30 and so on). We observe whether there is a significant increase in trading volume of the observed stocks through the “*Recon t*” and “*Recon t-1*” variables, whereas the “*Joiner*” variable indicates if there is a significant increase in trading volume specifically for stocks that are being added to an index. If the “*Joiner*” variable is negative, it indicates that the result pertains to stocks that are leaving an index instead. The results in table 3 show that there are no statistically significant increases in trading volume for added or dropped stocks on the reconstitution day itself (*t*), where we even observe a statistically significant decrease in the OMXN40 index.

In table 4, we observe that there is a statistically significant increase in trading volume during the day before the reconstitution day (*t-1*) for stocks that are added or dropped in all indices except OMXNLCEURGI at the 1% significance level. The increase varies from 16.1% for stocks in the OMXN40 index, to 179.4% and 185.7% for stocks in the OMXS30 and OMXH25, respectively. These amounts can be contrasted to those found on studies of the U.S. market, where daily trading volume levels around reconstitution are found to be ranging from 370% for the Nasdaq 100 up to 1320% for the Russell 2000 (Chinco and Sammon, 2022).

4.2. The amount of index-linked AUM

Next, we illustrate tables that describe the outputs of equations 6, 7 and 8. These establish how much of the trading volume on the day before and the day of the reconstitution of an index is due to passive investors trading on the indices’ reconstitutions. In this section, we present the descriptive statistics of our findings in a descriptive table, we present histograms to illustrate the nature of our data, and we show the results of our regressions on the AUM connected to the indices of our study.

Table 5. Excess AUM as percentage of market capitalization for t-1

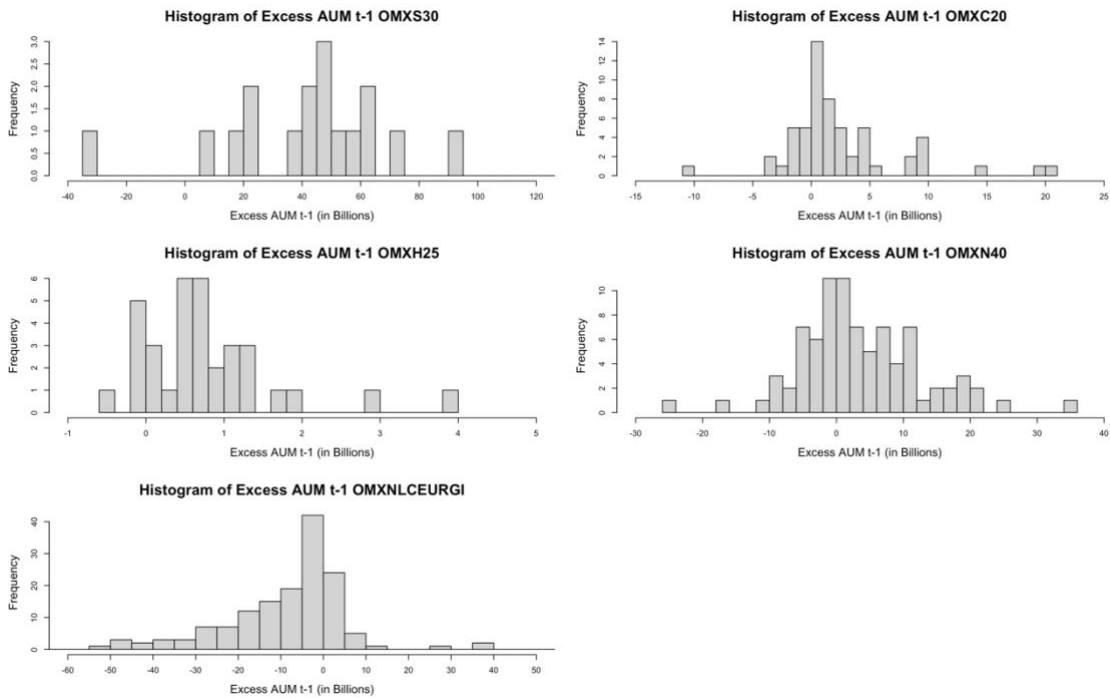
	<i>Dependent variable:</i>					
	Excess AUM t-1/Mkt Cap t-1					
	S30 (1)	C20 (2)	H25 (3)	N40 (4)	NLCEURGI (5)	BLEND (6)
Constant	0.0109 (0.0018) p = 0.00002***	0.0016 (0.0005) p = 0.0012***	0.0064 (0.0009) p = 0.000000***	0.0051 (0.0018) p = 0.0044***	-0.0028 (0.0044) p = 0.5178	0.0046 (0.0008) p = 0.000000***
Observations	17	58	29	85	152	194
<i>Note:</i>					*p<0.1; **p<0.05; ***p<0.01	

Table 6. Mean and descriptive statistics of AUM measurements at t-1 in billions

Index	Nobs	Mean	Median	Min	Max	1 st Quartile	3 rd Quartile
OMXC20	58	2.52	1.10	-10.10	20.89	0.10	3.84
OMXH25	29	0.92	0.73	-0.53	3.85	0.41	1.19
OMXN40	85	3.60	1.92	-24.71	34.97	-1.67	8.32
OMXNLCEURGI	152	-4.79	-4.78	-260.81	878.65	-16.59	-0.17
OMXS30	17	41.40	45.15	-30.32	92.46	20.62	59.98

Note: The numbers in each column refer to the measured AUM sums in the domestic currency of each index. The number of observations excludes an extreme value for OMXS30.

Figure 2. Histogram of excess measured AUM per index in billions



Note: The excess AUM always refers to the domestic currency of each index. In the case of OMXS30 and OMXNLCEURGI, a total number of 6 outlier observations have been omitted for the sake of displaying the data, 1 from OMXS30 and 5 from OMXNLCEURGI.

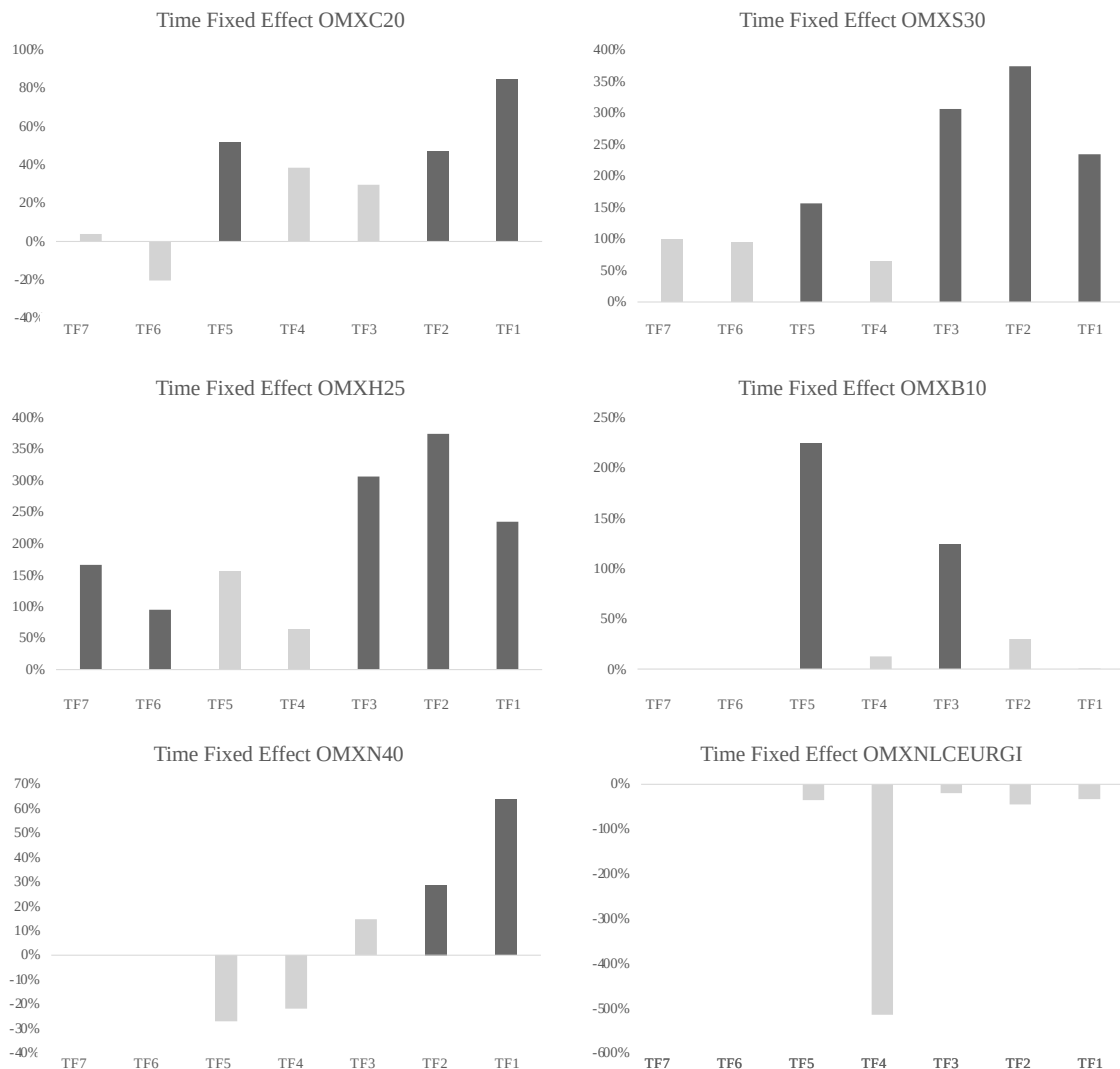
Firstly, table 5 presents the regression on the output of equation 8, that is, the term “ExcessAUMas%ofMarketCap” with no dependent variable in the regression. This was done to find the mean, standard error, and significance of our excess AUM computations. As a biproduct, we also observed the time-fixed effect of these excess AUM calculations, where we included the years with two or more observations. These are presented in the appendix of this thesis but are not a core part of our study. We observe statistically significant results at the <1% significance level for OMXS30, OMXC20, OMXH25, and OMXN40, where each index displays an excess AUM level of 109 bps, 16 bps, 64 bps, and 51 bps, respectively. Beyond this, the “BLEND” index represents a holistic look at all indices except OMXCEURGI, due to its lack of significant increases in trading volume as presented in section 4.1. This illustrative proxy for our observed Nordic market also showed a statistically significant average of 46 bps at the <1% level. Table 6 presents general means and statistics of the excess AUM calculations, where we aim to provide more context to the data, while Table 7

illustrates the spread of the measured excess AUM across all our observations, to provide a holistic view of the most common excess AUM levels.

4.3. The level of passive investing has changed over time

In this segment, we present the results of the regressions that explore whether the number of passive investors has increased over time, both during the day before (t_{-1}) and the day of the reconstitution (t) of an index, i.e. the results of equations 9 and 10.

Figure 3. Bar/box plot



Note: The y-axis refers to the percentage of excess trading volume in each period, while the x-axis presents each of the 7 observed time frames for each index. Dark grey indicates a statistical significance of <5% while light grey denotes insignificant results.

In figure 3 above, we graphically illustrate the findings of the regression in table 7, where we observed the time-fixed effects of how excess trading volume has changed over time for each index. A dark grey bar indicates that period had a significant result for its amount, while a light grey indicates insignificant results at the $\leq 5\%$ significance level. Any empty timeframes indicate a lack of data for that period.

Table 7. Regression output of time-fixed effects: day of reconstitution

	<i>Dependent variable:</i>					
	C20 Vo/ Avg _{t-15:t-2} (1)	S30 Vo/ Avg _{t-15:t-2} (2)	H25 Vo/ Avg _{t-15:t-2} (3)	B10 Vo/ Avg _{t-15:t-2} (4)	N40 Vo/ Avg _{t-15:t-2} (5)	NLCEURGI Vo/ Avg _{t-15:t-2} (6)
Joiner	0.035 (0.031)	0.125 (0.076)	0.103 (0.075)	0.105 (0.068)	-0.031 (0.021)	0.180 (0.138)
TimeFrame1	0.967*** (0.059)	0.983*** (0.102)	1.416*** (0.120)	0.950*** (0.114)	0.919*** (0.030)	1.047*** (0.126)
TimeFrame2	1.001*** (0.039)	1.063*** (0.114)	0.980*** (0.168)	0.827*** (0.085)	0.917*** (0.021)	0.922*** (0.170)
TimeFrame3	0.993*** (0.051)	1.060*** (0.150)	1.254*** (0.168)	1.005*** (0.078)	0.948*** (0.023)	0.965*** (0.156)
TimeFrame4	0.922*** (0.035)	0.935*** (0.128)	1.055*** (0.093)	0.824*** (0.067)	0.927*** (0.028)	5.507*** (0.582)
TimeFrame5	0.986*** (0.037)	1.102*** (0.088)	1.144*** (0.096)	1.051*** (0.091)	0.999*** (0.033)	1.173*** (0.326)
TimeFrame6	1.126*** (0.066)	1.236*** (0.112)	1.468*** (0.089)			
TimeFrame7	0.997*** (0.046)	1.035*** (0.102)	1.240*** (0.090)			
TimeFrame1 x Recont _t	-0.225 (0.298)	0.173 (0.472)	0.077 (0.579)	0.469 (0.559)	-0.092 (0.146)	-0.324 (0.477)
TimeFrame2 x Recont _t	0.078 (0.181)	0.055 (0.558)	0.318 (0.819)	0.351 (0.396)	-0.148 (0.091)	-0.080 (0.670)
TimeFrame3 x Recont _t	0.027 (0.249)	0.050 (0.721)	0.314 (0.819)	0.091 (0.349)	-0.043 (0.105)	-0.217 (0.607)
TimeFrame4 x Recont _t	-0.023 (0.168)	0.296 (0.624)	0.018 (0.460)	0.445 (0.323)	-0.186 (0.136)	-4.732 (2.881)
TimeFrame5 x Recont _t	0.176 (0.172)	0.471 (0.416)	0.623 (0.438)	-0.108 (0.427)	-0.037 (0.164)	-0.445 (1.663)
TimeFrame6 x Recont _t	-0.393 (0.321)	-0.451 (0.510)	0.465 (0.418)			
TimeFrame7	0.020 (0.218)	0.275 (0.472)	-0.042 (0.409)			
Observations	2,548	1,066	2,886	1,872	2,704	4,238
R ²	0.629	0.470	0.311	0.317	0.748	0.092

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 8. Regression output of time-fixed effects: day before reconstitution

	<i>Dependent variable:</i>					
	C20 Vo/ Avg _{t-15:t-2} (1)	S30 Vo/ Avg _{t-15:t-2} (2)	H25 Vo/ Avg _{t-15:t-2} (3)	B10 Vo/ Avg _{t-15:t-2} (4)	N40 Vo/ Avg _{t-15:t-2} (5)	NLCEURGI Vo/ Avg _{t-15:t-2} (6)
Joiner	0.035 (0.031)	0.125* (0.072)	0.103 (0.073)	0.105 (0.068)	-0.031 (0.021)	0.180 (0.138)
TimeFrame1	0.925*** (0.059)	0.900*** (0.097)	1.297*** (0.117)	0.968*** (0.112)	0.891*** (0.030)	1.047*** (0.126)
TimeFrame2	0.986*** (0.039)	0.922*** (0.108)	0.886*** (0.165)	0.829*** (0.084)	0.901*** (0.020)	0.936*** (0.170)
TimeFrame3	0.983*** (0.051)	0.945*** (0.142)	1.155*** (0.165)	0.961*** (0.077)	0.940*** (0.023)	0.964*** (0.156)
TimeFrame4	0.907*** (0.035)	0.922*** (0.121)	1.039*** (0.091)	0.836*** (0.067)	0.929*** (0.028)	5.523*** (0.582)
TimeFrame5	0.973*** (0.037)	1.060*** (0.084)	1.134*** (0.094)	0.960*** (0.090)	1.008*** (0.033)	1.170*** (0.326)
TimeFrame6	1.119*** (0.066)	1.183*** (0.106)	1.374*** (0.088)			
TimeFrame7	0.996*** (0.046)	1.008*** (0.097)	1.175*** (0.088)			
TimeFrame1 x Recont _{t-1}	0.846*** (0.296)	2.347*** (0.447)	3.189*** (0.567)	0.003 (0.554)	0.637*** (0.145)	-0.335 (0.477)
TimeFrame2 x Recont _{t-1}	0.473*** (0.180)	3.740*** (0.529)	2.779*** (0.801)	0.301 (0.392)	0.286*** (0.090)	-0.447 (0.670)
TimeFrame3 x Recont _{t-1}	0.296 (0.248)	3.064*** (0.683)	2.883*** (0.801)	1.235*** (0.345)	0.147 (0.104)	-0.202 (0.607)
TimeFrame4 x Recont _{t-1}	0.384** (0.167)	0.643 (0.591)	0.431 (0.450)	0.128 (0.320)	-0.218 (0.135)	-5.148* (2.881)
TimeFrame5 x Recont _{t-1}	0.520*** (0.171)	1.565*** (0.394)	0.871** (0.428)	2.247*** (0.423)	-0.270* (0.163)	-0.356 (1.663)
TimeFrame6 x Recont _{t-1}	-0.205 (0.320)	0.950** (0.483)	2.933*** (0.409)			
TimeFrame7 x Recont _{t-1}	0.040 (0.217)	0.984** (0.447)	1.664*** (0.401)			
Observations	2,548	1,066	2,886	1,872	2,704	4,238
R ²	0.634	0.525	0.340	0.331	0.751	0.092

Note:

* p<0.1; ** p<0.05; *** p<0.01

In table 7 and 8, we present the regressions for each index's time-fixed effects, i.e. how the trading volume on reconstitution day and the day before has changed over time. Once again, the index names are shortened to omit the "OMX" tag (i.e. S30 instead of OMXS30 and so on) for ease of reading. "*Joiner*" refers to the joiners of each index and captures the difference between joiners and leavers, who in-turn are captured in the intercept. Through this variable, it becomes evident that joiners of the OMXS30 and OMXH25 showed a statistically significantly larger increase in volume during t than leavers of those same indices, when controlling for the time-fixed effects. On $t-1$, however, there is no significant difference in the increase or decrease in trading volume when comparing joiners to leavers of the indices, when controlling for the time-fixed effects. The "*TimeFrame x Recon*" variable illustrates whether there is a significant level of increase in trading volume on t or $t-1$ for the stocks added and dropped to an index over time. As these regressions were run without intercepts, that is captured in the other variables. This setup enables us to observe the time-fixed effect on exclusively t and $t-1$. Reiterating the structure presented in section 3.4.2 "Structure of empirical and statistical analysis", the timeframes refer to the following intervals:

- 1 = 2021 – 2024
- 2 = 2017 – 2020
- 3 = 2013 – 2016
- 3 = 2009 – 2012
- 5 = 2005 – 2008
- 6 = 2001 – 2004
- 7 = 1997 – 2000

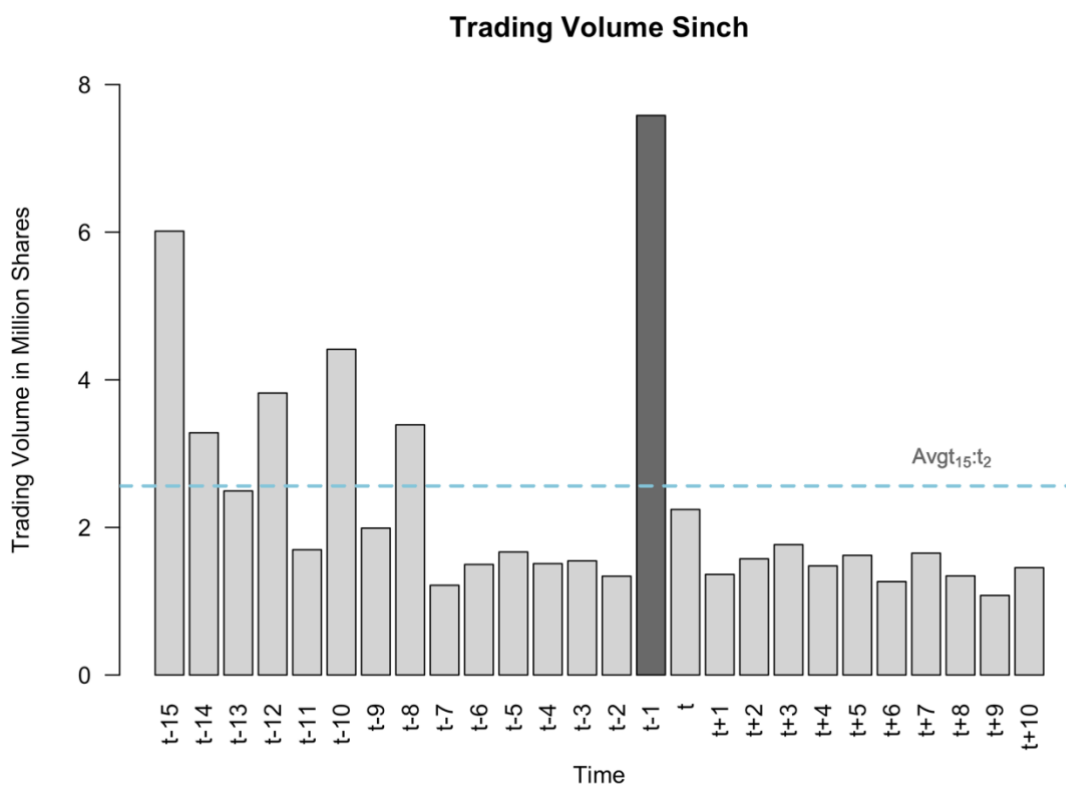
The results in table 7 show how there are no statistically significant increases in trading volume for added or dropped stocks during the reconstitution day (t) over time, which aligns with the lack of significant increases at the $<5\%$ level from table 3. However, in table 8, we do observe a statistically significant increase in trading volume over time at the $<1\%$ and $<5\%$ levels for all indices except OMXNLCEURGI, which does not present any significant results. Most notably, OMXC20 appears to have a significantly larger increase in trading volume during timeframe 1's 84.6%, as compared to timeframe 2's 47.3%, timeframe 4's 38.4%, and 5's 52.0%. For OMXS30, even though timeframe 1's 234.7% represents a decrease from timeframe 2's 374.0% and 3's 306.4%, they are all significantly larger than timeframe 5, 6 and 7's 156.5%, 95.0%,

and 98.4%, respectively. Similarly, OMXH25 shows an increase in trading volume over time, when comparing timeframes 1, 2, and 3's 318.9%, 277.9%, and 288.3% to timeframe 5's 87.1% and 7's 166.4%, with timeframe 6's 293.3% showing a standout increase in the early 2000s. OMXB10 shows no recent significant results, with its only periods of statistical significance being in timeframe 3's 123.5% and 5's 224.7%, where we actually observe a decrease in excess trading volume. Lastly, the OMXN40 shows a notable increase from 28.6% to 63.7% from period 2 to period 1.

4.4. Additional studies

In this final part of our descriptive statistics, we present our additional findings, done to provide additional context to our three main studies. Here we include the results as described in section 3.4.2 "Structure of empirical and statistical analysis", intertwining it with a more thorough description of Sinch (SINCH.ST) and Securitas (SECUB.ST). Firstly, we present graphs of the two stock's trading volume over time:

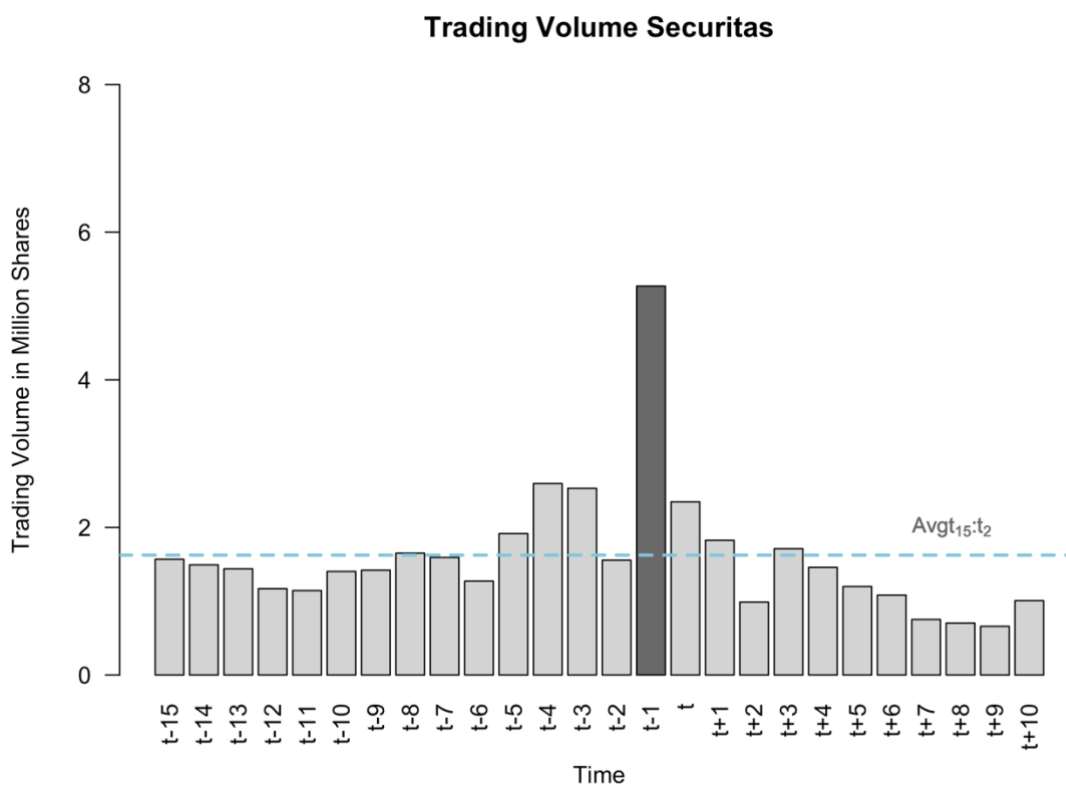
Figure 4. Graph of increase in Sinch’s trading volume the day before reconstitution



Note: The blue line refers to the average trading volume over the period prior to the day before reconstitution, t_{-1} , i.e. t_{-15} to t_{-2} .

Evidently, figure 4 illustrates a clear increase in trading volume of Sinch’s shares on day t_{-1} that greatly exceeds the trading average of the period, with Sinch’s daily volume on t_{-1} hitting 7.58 million, a 196% increase as compared to the average of 2.56 million.

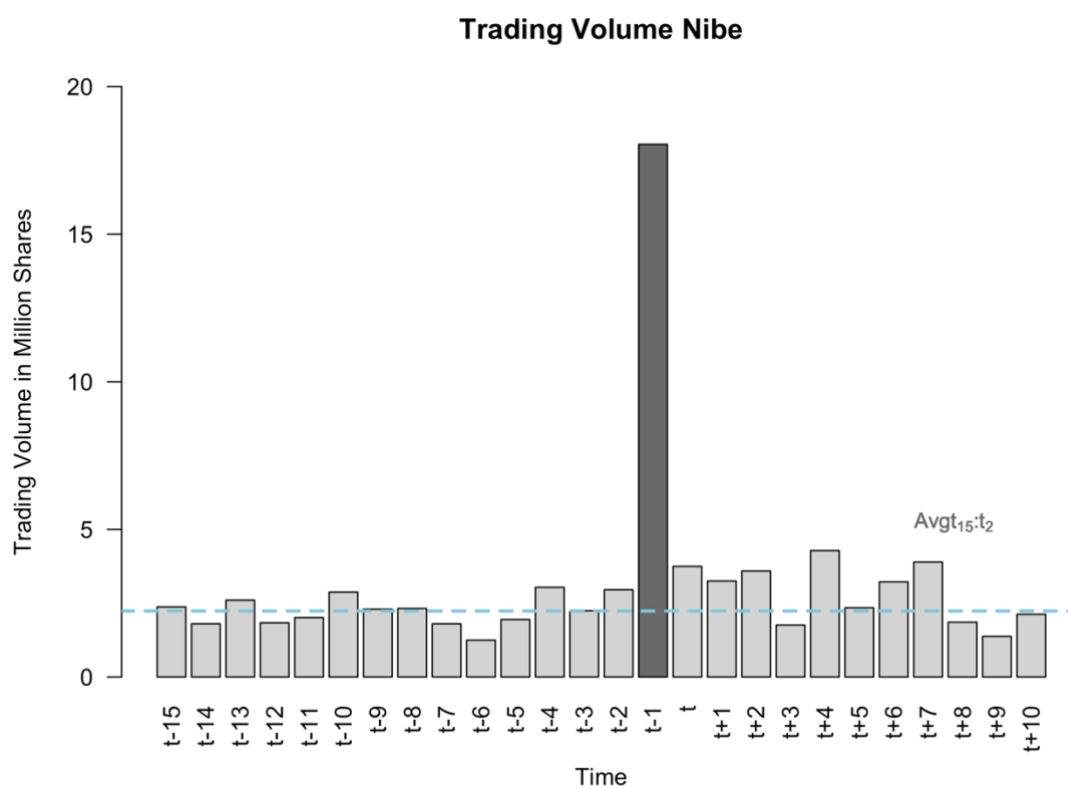
Figure 5. Graph of increase in Securitas' trading volume the day before reconstitution



Note: The blue line refers to the average trading volume over the period prior to the day before reconstitution, t_{-1} , i.e. t_{-15} to t_{-2} .

Notably figure 5 shows a similar result for Securitas as for Sinch, with there being a drastic increase in trading volume on day t_{-1} as compared to the trading volume of every other day as well as the average of the period, with Securitas' daily volume on t_{-1} reaching 5.27 million, a 224% increase as compared to the average during the period of 1.63 million.

Figure 6. Graph of increase in Nibe's trading volume the day before reconstitution



Note: The blue line refers to the average trading volume over the period prior to the day before reconstitution, t_{-1} , i.e. t_{-15} to t_{-2} .

Figure 6 demonstrates how Nibe's stock experienced a huge increase in the trading volume that far exceeds the average. Specifically, we observe a level of 18.04 million shares traded on t_{-1} , as compared to the average of 2.24m. This represents a 705% increase, and illustrates a significant gap to the results for Securitas as for Sinch,

5. Results and discussion

In the following section, we present the most relevant results from our findings in section 4. “Descriptive statistics”. We discuss the outcomes of each of the four sections of our study in-depth, explaining the causes for, and implications of, our findings.

5.1. Study 1: The increase in trading volume on reconstitutions

As presented in section 4.1., we found that there were no statistically significant increases in trading volume for added or dropped stocks during the reconstitution day itself (t), even finding a statistically significant decrease in the OMXN40 index at the 5% level. We did, however, see a drastically different view when observing the day before reconstitution ($t-1$), where we observed that there is a statistically significant increase in trading volume for stocks that are added or dropped in all indices except OMXNLCEURGI at the 1% significance level.

Most notably, there was an especially large increase in trading volume for OMXS30, at 179.4% and OMXH25, at 185.7%, with OMXC20 and OMXB10 exhibiting prominent increases as well, with 37.3% and 77.9% respectively. These levels are comparable to what Chinco and Sammon found in the U.S. (albeit much lower, possibly as a function of the Nordics being a smaller market and having fewer passive investors following the indices, overall), where they established increases in daily trading volume levels around reconstitution to be ranging from 370% for the Nasdaq 100 to 1320% for the Russell 2000 (Chinco and Sammon, 2022). This might indicate that passive investor behavior in the Nordics, at least when observing the most prominent domestic indices of each country, is similar to how passive investors in the U.S. trade on reconstitutions of their most major indices.

Our more general indices, that do not focus on one single country were not as clear, with OMXNLCEURGI not showing any significant increase, and OMXN40 only exhibiting a small increase of 16.1%. One cause for this could be that passive investors in the Nordics might prefer to focus on the most prominent indices for each country, rather than a large and broad one like OMXNLCEURGI, when choosing which index's moves to follow for their passively invested portfolio. Another possible takeaway is that Nasdaq's policy on publishing reconstitutions at least five days in

advance, along with doing its reconstitutions effectively in between $t-1$ and t (as it is immediately done at market open), contributes to more movement the day before the reconstitution, with passive investors wanting to get ahead of the reconstitution in order to match with the index at market open on reconstitution day, as such, doing all their trades on the day before the reconstitution. This is particularly evident when observing an index like OMXN40, which exhibits a statistically significant decrease in trading volume on t , while showing the previously mentioned increase of 16.1% on $t-1$, both at the $<5\%$ significance level.

An anecdotal but nevertheless interesting final takeaway from observing the timing of the reconstitutions in conjunction with which indices showed a significant increase in trading volume versus those that did not. OMXN40 and OMXNLCEURGI both reconstitute at the end of December, and presented the smallest increase, and the only insignificant change in trading volume, respectively. This could be due to the significant decrease in trading that always occurs around the holidays, where global equity markets tend to trade at 45-70% of its normal volumes starting Dec. 23 and do not return to normal volumes until a few days after New Year's Day (Frink, 2021).

Nevertheless, we clearly observe a pattern of increasing trading volume for stocks that are the subject of an index reconstitution, indicating that the market does pay attention to index reconstitutions. Having established this investor behavior, it mandates a measurement of exactly how much AUM is tracking these reconstitutions, put differently, a reassessment of the amount of index-linked AUM, which is presented in the following section.

5.2. Study 2: The amount of index-linked AUM

Section 4.2. illustrated how we measured the levels of excess AUM linked directly linked to each of the indices, where we found statistical significance for minor levels of excess AUM for the OMXC20, OMXH25, OMX40 and the broad proxy, "BLEND", where the OMXS30 showed the largest statistically significant excess level of AUM, though still at a small average of 109 bps at the $<1\%$ level. These levels of excess AUM's are measurements of the level of passive ownership in the companies included in each respective index is traceable to passive investment that specifically tracks each index. As such, the interpretation of 109 bps of OMXS30 is that 1.09% of the market

cap of stocks included in the OMXS30 index is owned through passive investors specifically following the OMXS30.

Naturally, this appears to be a low level of passive ownership when contrasting it to the levels of passive ownership in the U.S. market at 33.5% (Chinco and Sammon, 2022), however, when accounting for the nature and composition of the observed indices it makes more sense. As the main U.S. indices are considerably more sizeable in terms of the number of stocks they contain, compared to Nordic ones, with an index like the OMXS30 only having 30 components as compared to the Russell 1000 having 1000 components. Given this smaller number of components, the number of observations per reconstitution will often be fewer for the Nordic indices as well, which, in turn, leads to a smaller sample size and increased limitations on analyses.

Another explanation for this discrepancy could stem from possible structural differences between the U.S. and Nordic indices. Per construction, the Nordic indices have fewer constituents, leading to larger portfolio weights which, in combination with the smaller increases in trading volume produces lower values when measuring excess AUM. Nevertheless, one takeaway from this result, despite the low levels across the board, is that the indexes with the highest excess trading volumes on the day before reconstitution from study 1 also showed the highest levels of excess AUM as a percentage of market capitalization.

5.3. Study 3: The levels of passive investing over time

In section 4.3., we presented that all indices aside from OMXNLCEURGI and OMXB10 indicated that their reconstitutions create somewhat of an increase in excess trading volume over time, with OMXC20 having a significantly larger increase in excess trading volume from most recently timeframe 1's 84.6% to 5's 52.0%, OMXS30 at 234.7% most recently as compared to timeframe 7's 98.4%, OMXH25 timeframe 1's 318.9%, to timeframe 7's 166.4%, and OMXN40 which an increase from 28.6% to 63.7% from period 2 to period 1. The most prominent takeaway from this pattern is that the amount of excess trading volume on the day before reconstitution has typically increased over time in the Nordics, confirming that investors are more willing to invest in indices and that more Nordic investors, at large, are behaving in a passive investment pattern at present than historically.

5.4. Additional findings

Having concluded the three studies that comprised this thesis, in order to add a more contextual perspective to especially the findings in section 5.1, a brief case study on Sinch, Securitas, and Nibe from the OMXS30 index was launched. In this study, we observed the trading volumes of both stocks in detail over the reconstitution that both stocks were a part of on the 1st of June in 2021.

Evidently, figure 4 and 5 both illustrated a clear increase in trading volume of both Sinch's and Securitas' shares on day $t-1$ that greatly exceeds the trading average of the period, with Sinch's daily volume on $t-1$ hitting 7.58 million, a 196% increase as compared to the average of 2.56 million and Securitas' daily volume on $t-1$ reaching 5.27 million, a 224% increase as compared to the average during the period of 1.63 million. The main insight this provides us with, in addition to the learnings from section 5.1., is that the impact of index reconstitutions is tangible even on a single observation level, rather than on index level. We clearly see that both stocks experience increases in volume on the day before reconstitution, but not on the actual reconstitution date, visualizing our findings from section 5.1. regarding the timing of the passive trading relating to a reconstitution on a granular, single-stock level.

Interestingly, when observing Nibe during its addition to the OMXS30, the increase in trading volume was far higher, with a volume 705% over the daily average, as compared to the 196% and 224% we observed for Sinch and Securitas, respectively. This can likely be applied to the circumstances around the addition of Nibe being quite unique, as mentioned in section 3.4.2. On the 17th of November 2022, Nasdaq removed Swedish Match from the OMXS30 due to a public bid by Philip Morris International, in line with the deletion policy for the OMXS30 index methodology (Nasdaq, 2024). At the time of removal, Philip Morris held approximately 86% of the stocks in Swedish Match and had publicly stated their intention to complete the acquisition. It was also decided that a replacement for Swedish Match would not be included in the index until its regular, semi-annual, reconstitution on the 2nd of January 2023. Thus, when Swedish Match was ultimately removed, it was uncertain which stock would become the new 30th component (Hultgren 2022). With just over a month until the formal announcement of the new constituent list, there was limited time and uncertainty for passive investors who follow the OMXS30 but might prefer to make their trades in advance of the actual

reconstitution and, while Nibe was publicly known as a strong and likely candidate for the replacement of Swedish Match, Orrön Energy was also under heavy consideration (Andersson, 2022). As evident from our index datasets used for the other sections of our study, Orrön Energy had even previously been a constituent of the OMXS30 for 10 years, having been added on the 3rd of January 2008 and subsequently removed on the 2nd of January 2018.

While the uncertainty regarding the new index inclusion lingered, the final announcement of Nibe being the chosen stock was not made until after the market close on the 22nd of December 2022. Ultimately, this left investors with just 5 trading days from the time of the official announcement to the reconstitution date upon which the replacement became effective. Considering that this was during the December holidays, where the levels of trading drop regardless (Frink, 2021), one can assume this limited the time investors had to make any trades that tracking the OMXS30 in advance. Given that we observe a notably higher increase in trading volume at $t-1$ for Nibe compared other stocks around the time of reconstitution, as seen in figure 6 of section 4.4., one can speculate that some passive investors tracking the indices we have analyzed might normally make their trades multiple days in advance of the reconstitution date, due to the predictability of which stocks will be added or removed.

These findings are similar to what Chincó & Sammon (2022) find in a similar case study, where they observed the addition of Tesla to S&P 500 index. In that case, the addition similarly came as a surprise, leading to an increase of 4.2x Tesla's average trading volume on the reconstitution date. Thus, while we still find strong statistically significant increases in trading volume at $t-1$ for OMXS30, OMXC30, OMXH25, OMXB10 and OMXN40, a takeaway from this case study of Nibe is that these numbers could even be slightly underestimated due to some passive investors making their trades in advance of reconstitution, which bears implications for all three main sections of our study.

6. Conclusion and final remarks

Our thesis presents multiple findings regarding our research question “What is the prevalence of passive investing in the Nordic market?”, through our three studies, which were to:

1. measure whether there is a significant increase in trading volume on the day before ($t-1$) and the day of the reconstitution (t) of an index.
2. determine how much AUM that the trading volume on the day before ($t-1$) and the day of the reconstitution (t) implies are tracking each index.
3. investigate whether the amount of excess trading volume has increased over time, both during the day before ($t-1$) and the day of the reconstitution (t).

Our most prominent findings were that:

1. the largest significant increases in trading volume for the most prominent indices of each Nordic country occur on the day before reconstitution, rather than on the reconstitution day itself.
2. the major Nordic indices, where we found a significant increase in trading volume at $t-1$, are still small enough in terms of their number of components that passive investments specifically tracking those indices only represent a 0.85% share of their respective constituents' market capitalization.
3. the amount of excess trading volume, on the day before reconstitution, has typically increased over time in the Nordics, which verifies that more investors are behaving in a passive investment pattern at present than historically.

Nevertheless, for more scalable insights and to get an accurate representation of the entire level of passive investment in the Nordics, one could observe all indices that track some part of the Nordics, repeating our methodology from section 3.4.2., where they could measure the excess trading volume on the reconstitution days and quantify the levels of passive ownership that is directly traceable to each index. In theory, by holistically summarizing all indices that cover the Nordic market, one would end up with a quantification of the level of passive investment that captures the entire spectrum of passive investors, including those who are not publicly reported as such. This larger scope would enable more general insights and provide a foundation for examining

further implications of much of the literature mentioned in section 2.3. This is especially relevant to findings such as the inelasticity of the stock market increasing due to passive investing by Huebner, and Loualiche, et.al. (2021) and Sushko and Turner 's insights regarding the higher correlation between stocks and misallocation of capital due to passive fund managers' focus on systematic factors (2018).

Thus, our thesis is ultimately also about the methodology itself. As a result of the size and magnitude of our study, it serves to provide implications and a proof of concept of our approach, which we hope inspires further regional research on the subject of passive investing, at a grander scale with more resources.

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8. Appendix

Table 9. Time-fixed effect on excess AUM as a percentage of market cap

	<i>Dependent variable:</i>					
	Excess AUM t-1/Mkt Cap t-1					
	S30 (1)	C20 (2)	H25 (3)	N40 (4)	NLCEURGI (5)	BLEND (6)
Year2009	0.0079** (0.0031)					-0.0011 (0.0036)
Year2008		0.0016 (0.0025)				0.0016 (0.0081)
Year2010		0.0022* (0.0013)	0.0018 (0.0040)	-0.0003 (0.0070)		0.0013 (0.0030)
Year2011		0.0012 (0.0014)		0.0083 (0.0091)		0.0036 (0.0035)
Year2012		-0.0007 (0.0018)	0.0066 (0.0040)	0.0012 (0.0070)	0.0002 (0.0390)	0.0015 (0.0035)
Year2013		0.0011 (0.0025)	0.0029 (0.0040)	0.0026 (0.0050)	-0.0015 (0.0208)	0.0024 (0.0031)
Year2014		-0.0012 (0.0025)		-0.0124* (0.0070)	-0.0004 (0.0208)	-0.0042 (0.0038)
Year2015				0.0077 (0.0064)	-0.0068 (0.0166)	0.0072* (0.0043)
Year2016	0.0233*** (0.0038)	0.0003 (0.0015)	0.0044 (0.0040)	0.0263** (0.0111)	0.0110 (0.0126)	0.0092*** (0.0033)
Year2017	0.0165*** (0.0038)	0.0011 (0.0015)		0.0089 (0.0079)	-0.0045 (0.0142)	0.0063* (0.0033)
Year2018	0.0021 (0.0038)	0.0026* (0.0014)	0.0046 (0.0040)	0.0085 (0.0056)	-0.0032 (0.0275)	0.0052** (0.0026)
Year2019		0.0036* (0.0018)	0.0066* (0.0033)	0.0047 (0.0070)	-0.0120 (0.0184)	0.0048 (0.0033)
Year2020		0.0086*** (0.0025)		0.0055 (0.0038)	-0.0058 (0.0195)	0.0058** (0.0026)
Year2021	0.0076** (0.0027)	0.0025 (0.0021)	0.0062 (0.0040)	0.0066 (0.0070)	-0.0089 (0.0166)	0.0059* (0.0031)
Year2022	0.0114** (0.0038)	-0.0001 (0.0021)	0.0091*** (0.0023)	0.0118 (0.0091)	-0.0077 (0.0101)	0.0080*** (0.0031)
Year2023			0.0071 (0.0040)	0.0139** (0.0064)	0.0176 (0.0147)	0.0107*** (0.0036)
Year2024			0.0083* (0.0040)		-0.0156 (0.0142)	0.0083 (0.0081)
Observations	15	56	25	84	152	194

Note:

*p<0.1; **p<0.05; ***p<0.01