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An Event Study of the Index Effect: Evidence from the MSCI World Small Cap ex USA Index

Master's thesis

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Declaration of Authorship

I declare that I have worked on my master's thesis titled "An Event Study of the Index Effect: Evidence from the MSCI World Small Cap ex USA Index" by myself and I have used only the sources listed in the bibliography at the end of this thesis.

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Abstract

This thesis studies abnormal returns around the 2025 reconstitutions of the MSCI World Small Cap ex USA Index. The research is based on the quarterly reviews provided by MSCI, as well as LSEG Datastream daily total return data. Event-study methodology is applied in relation to changes within the index portfolio composition (additions and deletions). Abnormal returns are estimated with the Carhart four-factor model, accounting for the effects of the stock market, size, value and momentum. Abnormal returns are obtained, yet their direction differs from predictions related to the traditional index effect. In particular, additions of stocks are associated with negative abnormal returns, whereas deletions bring about positive cumulative abnormal returns in the long run, both measured relative to the Carhart predicted normal return. These results are not fully consistent with traditional hypotheses in the literature. A cross-country analysis is also provided and suggests heterogeneous effects across different regions, especially Europe, Australia and the United Kingdom.

Keywords

Index reconstitution; index effect; MSCI Indexes; MSCI World ex USA Small Cap Index; event study; abnormal returns; cumulative abnormal returns; Carhart four-factor model; small-cap; cross-country analysis

Title of Contents

1. Introduction

S&P 500, FTSE, or MSCI indexes are among the most well-known benchmarks in the domain of finance. These indices play a crucial role in portfolio management, as they are widely used by institutional investors such as pension funds, mutual funds, hedge funds, index funds, and insurance companies to guide asset allocation decisions. Over the past several decades, the growth of passive investment strategies has further increased the importance of such benchmarks. Passive funds seek to replicate rather than outperform the performance of a specific index, and their rapid expansion has made index composition a matter of growing interest to both practitioners and academics. This trend is reflected in the scale of index-based investing: index mutual fund assets grew from $98 billion in 1996 to $5.855 trillion at the year-end 2023, according to the Investment Company Institute (2025).

Institutional investors that track benchmark indices seek to replicate them with a high degree of precision, making the minimization of tracking error a central objective. Tracking error is commonly defined as the divergence between the return behaviour of a portfolio, here the index fund portfolio, and that of its benchmark (Chang et al., 2025). Because investors often evaluate the performance of index funds through this metric, material deviations from the benchmark may be interpreted as evidence of inefficiency in the following index (Ben-David et al., 2017). Consequently, changes in the index composition may compel institutional investors to rebalance their holdings, thereby generating significant demand or supply pressures in the underlying securities.

Index reconstitutions, therefore, constitute important events for multiple participants in the financial market. When a stock is added to or removed from an index, the event may trigger pronounced changes both stock returns and trading volume. These market reactions are commonly referred to as the index effect. Empirical studies generally identify two key dates associated with this process: the announcement date (AD), on which the index provider publicly discloses the upcoming revision, and the effective date (ED), on which the change is formally implemented. AD and ED are generally separated by a time window between 2 and

3 weeks, which corresponds to 12 to 15 trading days. This time span is usually smaller for the S&P500, with 5 trading days between ED and AD.

Between these two dates, the literature has documented a recurrent pattern in stock behavior. In most cases, stocks added to an index experience positive abnormal returns and increased trading volume, whereas stocks removed from an index tend to exhibit negative abnormal returns. While there is broad agreement regarding the existence of abnormal price movements around the index revision, the theoretical mechanisms that explain them remain contested.

The diversity of empirical findings can partly be attributed to methodological differences across studies. Factors such as the sample period, the event window, econometric specification, and theoretical framework may substantially influence the interpretation of the results. Despite these variations, most explanations of the index effect differ primarily with respect to one key dimension: whether the observed price impact is temporary or permanent.

Another important consideration concerns the choice of index examined. A large portion of the existing literature focuses on U.S. indices, particularly the S&P 500. Early studies such as Beneish & Whaley (1996), Shleifer (1986), Pruitt & Wei (1989), Amihud and Mendelson (1986), Harris and Gurel (1986), and Lynch and Mendenhall (1997) were among the first to document and analyze the rebalancing effects associated with changes in the S&P 500. Since then, this line of research has been extended to a wide range of international markets and indices. For example, Liu (2000) and Haneda & Sarita (2001) investigated the Japan's Nikkei index, while other studies have explored the CNX Nifty 50 (Selvam et al., 2012), the Toronto Stock Exchange 300 (Kaul et al., 2000), the DAX (Deininger et al., 2000), the AEX (Doeswijk, 2005) and the CNX Nifty 50 (Selvam et al., 2012).

Despite the breadth of the existing literature, relatively few studies focus on MSCI indices, and even fewer examine small capitalization indexes in isolation. This relative lack of attention is puzzling, given the global coverage and widespread use of MSCI benchmarks in institutional investment practice. Moreover, prior research suggests that abnormal returns associated with index rebalancing may vary significantly across countries (Chakrabarti et al., 2005; Chen et al., 2019). However, these studies rarely extend their analysis to indices composed of lower market capitalization stocks, thereby leaving an important gap in the literature.

A further limitation in the existing literature concerns the models used to estimate abnormal returns. Many studies rely on the market model, which offers a relatively simple framework for calculating abnormal returns but does not account for several potentially important determinants of stock performance. In particular, it omits factors related to firm size and momentum, both of which may be especially relevant when examining small-cap stocks. As a result, the use of more comprehensive asset-pricing models may provide a more accurate assessment of abnormal returns in the context of index rebalancing for small-cap indices.

The paper aims to contribute to the existing literature by examining the presence of abnormal returns surrounding the 2025 reconstitution event of the MSCI World Small Cap Index in 2025. More specifically, it addresses the following research question:

"Did the 2025 MSCI World Small Cap ex-US Index reconstitution lead to abnormal stock returns around the announcement and implementation dates?"

To answer this question, the paper employs an event study methodology specifically adapted to the characteristics of the small-cap stocks. Abnormal returns are estimated using the Carhart four-factor model, which augments the Fama-French three-factor model with a momentum factor. By combining a multifactor asset-pricing framework with a standard event study design, this paper aims to provide new evidence on the existence, magnitude, and persistence of the index effect in the small-cap segment of the market. In addition, focusing on the recent 2025 reconstitution period allows the analysis to contribute to the literature on the so-called diminishing or disappearing index effect, although the absence of earlier sample periods prevents a direct assessment of whether the effect has weakened over time (Greenwood & Sammon, 2023; Kappou, 2018).

The paper contributes to the literature in several ways. First, by focusing on an MSCI index, it addresses a segment of the index rebalancing literature that remains relatively underexplored, thereby opening avenues for future research, particularly with respect to cross-country differences. Second, the use of the Carhart four-factor model represents a methodological contribution, as prior studies often rely on simpler models to facilitate computation. Finally, the recent time period examined enhances the contemporary relevance of the findings and allows for a reassessment of competing explanations in the literature.

The paper begins by outlining the main trends and hypotheses identified in the empirical literature from the early 1970s to the present. It then describes the data sample and the criteria used for its selection. The section following the data sample selection presents the model and time windows employed in the event study, as well as their application to the case under analysis. The results are subsequently presented in a structure consistent with the actual data. The final section discusses the main results, as well as the limitations of the research, and suggests possible directions for improvement.

2. Literature review

This literature review is divided into three main sections. First, the efficient market hypothesis is introduced as the benchmark against which all rebalancing effects are evaluated. The reference framework and its limitations give rise to the various hypotheses explaining price reaction to rebalancing events, which are discussed in the second section. These include the Price Pressure hypothesis, the Information Content hypothesis, the Downward-sloping demand curve hypothesis or the Imperfect Substitution hypothesis, the Investor Recognition hypothesis, and the Liquidity Cost hypothesis. Finally, the third section provides a closer examination of the MSCI World Small Cap index, with particular attention to its construction and reconstitution methodology.

2.1 Efficient Market Hypothesis (EMH)

The literature on the index effect is extensive, though it relies on similar empirical approaches. For instance, most studies employed the event study methodology to measure abnormal returns around index announcements. This paper will not make an exception regarding the methodology. Most papers also refer to the same five main theories already mentioned above. However, some studies discuss only three or four, depending on their period of relevance. Before discussing the different explanations proposed in the literature, it is necessary to introduce the theory that motivates the divergence in index reconstitution effect: the Efficient Market hypothesis (EMH).

The concept of market efficiency was formalized by Eugene Fama in his paper "Efficient Capital Markets: A Review of Theory and Empirical Work". According to Fama (1970), "the primary role of the capital market is the allocation of ownership of the economy's capital stock" (p. 383). The author states that an efficient market is a market where companies are able to decide how to invest and produce, and investors choose their securities (e.g. stock, bonds) to buy, assuming that the price of those securities already includes all available information, independent of time. In such a market, securities prices are assumed to "fully reflect all available information". (Fama, 1970, p. 383)

From this perspective, the assumption that prices fully reflect available information relies on the idea that the conditions of market equilibrium can be expressed in terms of expected return. Within this framework, expected return theories assume that the equilibrium expected return of a security consists of a risk-free rate and a risk premium, where the premium reflects the level of risk associated with the security, given the available information. Prices, therefore, reflect all available information because the information is used by investors to determine the return they require for holding the given security.

Formally, Fama (1970) expresses this relationship as follows:

$$\mathbb{E}\left(\widetilde{p_{J,t+1}} \mid \Phi_t \right) = \left[1 + \mathbb{E}\left(\widetilde{r_{J,t+1}} \mid \Phi_t \right)\right] p_{jt}$$

where E is the expected value; p_{jt} constitutes the price of a stock j at time t, $\widetilde{r_{J,t+1}}$ denote the return (in per cent), Φ_t represent the "fully reflected" information. (Fama., 1970)

A key property of this theoretical framework is the fair game property. If markets are efficient, then investors cannot systematically earn abnormal returns using available information because the price already embeds that information. Within this theoretical context arises the issue addressed in the literature on the index effect. In principle, the inclusion of a stock into an index does not modify its fundamental characteristics, such as expected cash flow or risk.

Under the efficient market hypothesis, such an event should therefore not generate systematic abnormal returns. However, multiple studies such as Harris & Gurel (1986), Shleifer (1986), Beneish & Whaley (1996), Lynch & Mendenhall (1997), Chen et al. (2019) document significant price reactions following the stock inclusion or deletion around the announcement. These findings served as the basis for the development of the five theories previously mentioned. The following section reviews these different theories in detail.

In his paper, Fama also categorized the existing literature on the efficient market into three groups based on the type of information assumed to be reflected in prices. The first one, the "strong form", describes the situation in which investors have monopolistic access to any information relevant to price formation. Although this form is generally considered unrealistic, it can serve as a benchmark for economists who are looking to evaluate how the real markets differ from perfect efficiency. The second category, the so-called "semi-strong form", assumes that all publicly available information is fully incorporated into the asset price. While much of the index rebalancing literature finds evidence that is difficult to reconcile with semi-strong-form efficiency, some results are partially consistent with it, especially when considering the Information Content hypothesis (see section 2.3). The third category, known as the weak form, assumes that only past market information, such as historical price or return, is available. Fama notes that most empirical studies conducted at the time primarily focused on this form of market efficiency.

In essence, the efficient market hypothesis serves as the theoretical benchmark, while other hypotheses provide competing explanations for the abnormal returns observed around index rebalancing events. EMH specifies what should occur in an efficient market, whereas empirical studies either document deviation from this general framework or, in some cases, findings that remain consistent with it.

2.2 Price Pressure Hypothesis (PPH)

2.2.1 Origin

The Price Pressure Hypothesis was first formalized and empirically tested in the paper "The market for securities: Substitution versus price pressure and the effect of information on share price" (Scholes, 1972). It is introduced with the description of a noticeable trend: when an investor buys or sells a small quantity of any securities on a market, for example, the "New York Stock Exchange", it is assumed that the price of the stock will be set at the market price. However, when a trade involves the sale of a large volume of securities, the price of the security must fall in order to attract new investors. This inducement or this "sweetener" (Scholes, p. 180) is expressed as a temporary price discount or higher expected return. Indeed, when the supply of shares in the trade market increases, the market holds more shares than it can absorb, leading to a demand for higher compensation from the investors since it generates additional risk.

A key feature of the Price Pressure Hypothesis (PPH) is that price changes induced by large trades are temporary. The difference between the PPH and Fama's Efficient Market Hypothesis (EMH) lies in how short-term price deviations are interpreted. While EMH assumes that prices rapidly reflect all available information and that any deviations from fundamental value are quickly arbitraged away, the PPH argues that, in the short run, prices may temporarily deviate due to liquidity constraints. In particular, when large trades occur, market participants cannot immediately determine whether they are information-driven or simply due to portfolio rebalancing, and this uncertainty, combined with limited arbitrage, leads to temporary price pressure effects.

Another implication of this theory is that the extra profit it predicts can arise only "If the excess-demand curve for shares is downward sloping, …" (Scholes, 1972, p. 180). This assumption is crucial, as it is the condition that allows changes in demand generated by index revisions to influence stock prices. In this respect, a downward-sloping demand curve constitutes a fundamental condition for the PPH to hold. However, within the framework of the PPH, this effect is only temporary. Additional selling pressure leads to a decline in price, whereas additional buying pressure leads to an increase in price. Thus, under the PPH the downward-sloping demand curve reflects the impact of short-run order imbalances on prices, as investors require a price concession to absorb excess demand or supply. However, although Scholes is one of the first to employ this hypothesis, his findings do not fully support the temporary aspect of the PPH because the decline in price after a large sale of a block appears to be permanent rather than followed by a reversal effect as suggested in the PPH

At that time, an alternative view had already been advanced in support of the PPH. According to Kraus & Stoll (1972), findings on block trading demonstrate evidence of a distribution effect (similar to PPH). Price declined around secondary distribution and recovered after the transaction. The paper allows for a comparison because the secondary distribution employed in Scholes (1972), which involved the sale of a large number of shares already existing, is considered similar to a minus tick (block trade with lowered price initiated by the seller) since both involve a massive quantity of stock. The difference in results is explained by differences in institutional arrangements. Since secondary distribution involves an underwriter, an investment bank that commits to buying or selling the entire block of shares, the underwriter indirectly absorbs the risk of not being able to resell the shares. To bear the risk, the underwriter could charge high fees since there was no strict fixed commission rule at the time. Thus, selling through secondary distribution is much more expensive than a standard trade "Contrary to Scholes' assumption, commissions on secondary distribution are significantly higher than normal NYSE commission" (Kraul, 1972, p. 586). Since the underwriter handles the sale, the market does not need to adjust prices much, and no strong price pressure appears.

2.2.2 Price Pressure Hypothesis in index reconstitution

The early literature based on secondary distribution or block trade literature suffers from an important identification problem. Although Scholes (1972) found significant price drops following large sales, this evidence cannot be used as a discriminant factor between different price hypotheses. The literature informs us that this drop might be caused by adverse information generated during this transaction. Scholes (1972), aware of this issue, tries to modify the characteristics of the seller by calculating the price drop for estates or trusts that are known to trade essentially for liquidity reasons. The results demonstrate a weak price drop, but not null. None of the authors controls this information effect fully. Since the effect is not fully isolated, even liquidity-motivated trades may still be interpreted by the market as containing adverse information. To overcome this issue, it is necessary to examine events that are highly unlikely to convey new information, such as index rebalancing events. (Harris & Gurel, 1986).

The Standard and Poor's (S&P 500) change in composition is one of the first events used to furnish evidence of the existence of PPH. In addition to not conveying new information to the market about future returns, the shift in demand caused by index funds, which are trying to fit their portfolio to the index, will bring supplementary evidence about the PPH. Harris & Gurrel (1986) argue about the non-informational characteristics of changes in the S&P500 and bring new empirical results to the table, taking into account this non-informational assumption.

According to Harris & Gurrel (1986), most of the S&P500 changes reflect companies that face bankruptcy, merger, tender offer or firms that become too small (not representative enough of the US market). The company being deleted from the index is replaced, in most cases, by the largest company in the same sector which is not already part of the index. These changes are not made under an investment appeal, and the changes are based only on publicly available information. When the S&P 500 composition changes, index funds mimic the change by buying the added stock or selling the deleted stock. These transactions (35.7 billion in 1983 in public index funds) are large and generally happen a few days after the announcement. Since the announcement already brings the new information and that index funds generate a large change in demand, the empirical result should a priori bring new evidence in favor of the PPH.

The result obtained by Harris & Gurrel (1986) over rebalancing events from 1978 to 1983 indeed supports the PPH since a large increase in volume and price has been detected on the following trading day after announcement. The result obtained from 1973-1977 is a temporary mean excess return one trading day after the event of 0.21 per cent[1] for inclusion and 3.13 per cent between 1977 and 1983, which returns to pre-announcement levels after three weeks. The authors consider that during the earlier years, the development of index funds was still minimal, therefore it is unlikely that the announcement day caused the price change on its own.

Woolridge and Ghosh (1986), with their cross-comparison analysis of the Information content hypothesis, price pressure hypothesis, and liquidity cost hypothesis, find similar evidence for volume, in the case of stock inclusion, that supports the PPH theory, but obtain a permanent price increase, which is not

[1] Not statistically significant, t = 0.99

possible in PPH. The deletion results seem in accordance with the PPH, but the sample is relatively small, hence no conclusion can be made. In the same year, Arnott and Vincent (1986) also document price increases, but their analysis is limited to the 1980-1984 period. They report a 2.19% increase in return for added stocks and note that this increase is "sustained over the subsequent week and month" (Arnott and Vincent, p. 32). This finding is difficult to reconcile with the temporary reversal predicted by PPH. Although the authors do not take an explicit position on the PPH, their results remain relevant to the debate.

More recent research on the Chinese equity market, particularly on the CSI 300, supports the PPH. Wang et al. (2015), using data from 2005 to 2012, document an abnormal return of 0.54% for additions and -0.40% for deletions on the announcement day. They further show that the announcement gain for additions is fully reversed and that the price decline associated with deletions is fully reversed within 20 trading days. Chu et al. (2022) extend the analysis to a more recent period, 2010- 2019, while focusing on the CSI 300. Their results interpretations are broadly similar: from the announcement date to the effective date, additions (deletions) earn 2.19% (-2.23%), while from the effective date to fifteen days afterwards, they record -1.69% (-0.737%). These results indicate a strong, though not complete, reversal effect. One limitation of this second study is the relatively short post-effective window, since fifteen days may not be sufficient to capture the full reversal. Evidence from the Indian market points in the same direction. Marisetty (2025), examining the NSE NIFTY revisions over 2010-2024, also finds support for the PPH: The average abnormal return on the announcement day is +0.144% (-0.6184%) for additions (deletions), while on the effective day it is -0.1939% (0.5274%).

Despite the recent literature on specific indices, including indices from emerging markets, studies in which the PPH is the central focus remain relatively rare. The main trend in literature is that there is broad agreement that institutional investors' forced buying creates mechanical demand pressure, several papers dispute or only partially support the view that the resulting price effects are purely temporary.

2.3 The information content Hypothesis (ICH)

The second hypothesis is the Information Content Hypothesis, which was first formalized, once again, by Scholes (1972). The ICH can also be linked to Fama's (1970) efficient market hypothesis, although the two concepts are not identical. The EMH is a broad theory stating that security prices reflect available information, whereas the ICH provides a specific explanation for price reactions around particular events or trades. In this sense, the ICH can be understood as operating within the EMH framework. According to ICH, price changes around large trades are caused by the information that market participants infer from the trade itself. If a large investor sells, other investors may interpret the sale as a signal that the seller possesses negative private information; conversely, a large purchase may be interpreted as a positive signal. As a result, prices adjust rapidly to reflect the expected informational content of the trade. Unlike the PPH, the ICH implies a permanent price change, because the price movement reflects a revision in the market's assessment of fundamental value rather than a temporary order imbalance. Moreover, since information acquisition is costly, large traders are often assumed to be more likely to trade on information. This hypothesis fits best with Scholes' findings since he observed a negative price reaction around secondary distribution but no reversal pattern.

Other old papers like Kraus and Stoll (1972) or Dann et al. (1977) also mention the possibility that the price moves in accordance with the revelation of new information due to large trades. Recent literature tried to control this information effect through the study of index rebalancing, supposing that it brings no new piece of information since everything is publicly revealed. However, some papers differ from this general way of thinking and believe that the addition of a firm to the S&P index is a signal of a better future prospect for this firm. For instance, Jain (1987) tries to determine if abnormal returns due to the addition of the S&P 500 follow the ICH or the PPH. The authors use a company added to the S&P 500's supplementary indexes, which are not supposed to be tracked by index funds. The author found an excess return of 3.07%, and the control firms also obtained a positive excess return of 2.93%. The results do not support the PPH, therefore inferring the rightfulness of the information theory. Another example is Dhillon & Johnson (1991), which is confused by these divergences between PPH, ICH and imperfect substitution theory, offers another empirical analysis that, in the end, disproves the PPH and supports ICH and imperfect substitution theory (only if call, put, bond, and stock of a firm are all close substitutes for one another). Finally, Denis et al. (2003) test directly if inclusion is linked with new information about future firm performance. The authors analyzed EPS forecasts before and after inclusion and took a closer look at the earnings made after the stock was added relative to pre-inclusion expectations. Thanks to their empirical results, the authors conclude that firms recently added are more likely to experience upward revision in EPS forecasts. Although analysts' forecast errors are negative on average for all firms, the forecast errors for recently added stocks are less negative than those for comparable firms. This suggests that the realized earnings of added firms are relatively stronger for comparable firms. The authors therefore argue that inclusion in the S&P 500 is not information-free.

2.4 The downward sloping demand curve (DSDC) or imperfect substitution hypothesis

According to the imperfect substitution theory, stocks belonging to the S&P500 Index do not have a perfect substitute and have a downward-sloping demand curve in the long term, unlike the PPH. Each security could not possibly be replaced by a combination of other securities. Any price change is created to eliminate any excess demand, and there will be no reversal effect, the price evolution is permanent. (Kappou et al., 2008)

Shleifer (1986) is generally regarded as the foundational paper that explicitly applies the imperfect substitution hypothesis or DSDC hypothesis. As most of the literature around the index effect, Shleifer (1986) acknowledges the buying pressure (increase in demand) created by index funds, whose need to buy the new stock added to the index. However, Shleifer (1986) goes further by analyzing whether the demand curves of stock are horizontal, as most of the literature assumes, or if they are downward sloping. His study tries to determine any price effect during the rebalancing event of the S&P500 in order to isolate the information effect at the image of Harris & Gurel (1986). The intuition is that if the demand curves are horizontal, that extra demand should not move the price much because investors are willing to absorb additional shares at the same price. On the other hand, if the demand slopes down, then the price should rise. The sample date (1966-1983) of the empirical study is divided into two: 1966-1975 and September 1976-1983. This division has not been made randomly. September 1976 is a special month because it is when S&P began publicly announcing index changes in advance through a system of notifications for subscribers. Prior to September 1976, changes in the index were recorded monthly without specifying the exact date. This distinction in his study is important because it enables to be more precise about the exact announcement day, which is of utmost importance considering that the study looks at whether prices react when the market first learns that a firm will be added to the index.

The main findings are that after September 1976, there was a gain of 2.79% around the announcement date, while results before 1976 are statistically insignificant. This difference is explained by a growth in index funds over time. The abnormal return did not show any significant sign of reversal after 10 to 20 days of trading, which is considered not temporary by the author (Shleifer, 1986).

A few years later, in 1989, S&P changed its methodology again and began announcing index changes one week before they became effective. This change in timing offers a new perspective to the literature because it separates the announcement date from the effective date, making it possible to study whether prices adjust immediately to public information or continue to drift afterwards. The results under this new methodology are related to the semi-strong form of market efficiency, since all publicly available information should already be incorporated into trading prices at the announcement. In this context, Lynch and Mendenhall's (1997) empirical result demonstrates that additions have a positive abnormal return on the announcement day and during the period following until the effective date (3.8%). Then shows negative abnormal returns (-2.106%) after the stock is actually added[2]. Deletions show the mirror image, negative abnormal return after the

[2] Window used after the implementation is CD to CD+7

announcement date until the effective date and then a positive abnormal return after deletion. Hence, unlike Shleifer (1986), the paper supports the reversal effect after the effective date and, by extension, the temporary effect required in PPH. Nevertheless, Lynch and Mendenhall (1997) still strongly support the imperfect substitute because, according to their results, the reversal is not complete, making space for the DSDC long-term hypothesis: "We also find that, for additions, the cumulative abnormal return from the day following the announcement through the price reversal is weakly positive. We interpret this abnormal return as a lower bound on the price effect caused by index-fund trading in the presence of downward-sloping long-term demand curves." (Lynch & Mendenhall, 1997, p. 381). Finally, they find strong evidence of a permanent effect for deletion, while for addition, the permanent effect is much weaker and not statistically significant in the post-announcement window.

Beneish and Whaley (1996) analyze the same post-1989 institutional setting but place greater emphasis on the mechanism generating the price effects. They argue that advance notice created the conditions for the “S&P game” in which risk arbitrageurs buy newly announced additions ahead of index funds and sell to them, presumably at a higher price, a few days later, around the effective date. Concretely, they obtain similar results with a rise in abnormal return from the close of the announcement day to the effective day, with a larger effect after the new S&P announcement policy. These abnormal returns are partially reversed but not totally, which is also the case in Lynch and Mendenhall (1997).

More recently, Wurgler and Zhuravskaya (2002) supported the imperfect substitute theory with similar results as previous studies but brought a new interpretation. According to them, arbitrage fails to eliminate these price effects because, in reality, stocks do not have perfect substitutes. Therefore, an arbitrageur who buys the mispriced stock and shorts a similar stock still bears residual risk. That risk makes arbitrage less aggressive. Market anomalies persist because arbitrage is too risky to correct the mispricing fully. They emphasize that their opinion is particularly relevant for small-caps, where arbitrage risk is even higher, which is especially relevant for our paper.

Several other studies expand the DSDC hypothesis through methodology differentiation, such as Kaul et al. (2000) with a 2.3% raise in the price of stock around the Toronto Stock Exchange (TSE300) without a reversal effect, or again Chakrabarti et al. (2005) which supports the downward sloping demand curve view by comparing the abnormal return within several countries through the MSCI Standard Country Indices reconstitution event.

As a final point, it is important to distinguish between a short-run and long-run downward sloping demand curve, since this is a common source of confusion. A short-run DSDC can arise under both PPH and the imperfect substitution hypothesis: in both cases, a surge in demand raises price at the time of rebalancing. The difference lies in persistence. Under the PPH, the price increase is only temporary: index funds and other benchmark tracking investors generate a surge in demand for stocks added to the index. To absorb this order imbalance, other investors must be induced to sell through a temporary price increase. Under the imperfect substitutes hypothesis, by contrast, the added stock cannot be fully replaced by other securities; consequently, the demand shock leads to a new equilibrium price, implying no full reversal in the long run.

2.5 Investor Recognition Hypothesis

The Investor Recognition hypothesis is a relatively new explanation for anomalies in the price. The literature starts with Merton (1987), who questioned the CAPM assumption that investors know about all securities, while in fact, investors only pay attention to a limited subgroup of firms. Merton is aligned with the concept of limited or bounded rationality presented by Simon (1955), which implies that investors are not perfect rational agents because they have limitations such as a limited awareness or information, and cognitive capacity. Merton's model indeed acknowledges that investors are aware only of a part of the shares, and the content of their portfolio reflects this limited knowledge by holding only known stocks. This assumption implies that the stock must offer a higher expected return due to a limited demand. Equivalently, the stock price is lower than it would be under full information. His result indicates an extra premium due to incomplete information that will be interpreted as "the shadow cost of information” (Merton, p. 491). The result also demonstrates that the smaller the number of investors who know about the stock, the larger the premium is.

From his work derives the investors' recognition hypothesis in the context of the rebalancing event first mentioned by Chen et al. (2004). Chen’s empirical study on the price effect around S&P 500 constitution changes results in an increase in price with no reversal effect, which has already been related in the imperfect substitution theory. However, their analysis differs in terms of deletion results, which are considered not permanent. Interpretations deviate from prior beliefs of the DSDC hypothesis and liquidity hypothesis (see 2.6), where the addition effect creates a positive increase in price symmetrical to the decrease effect created by deleted stocks. The potential interpretation of this result change is the asymmetry of information awareness. When a stock is being added to an index, it gains in awareness among the investors, therefore creating a permanent increase in price. While being deleted creates a loss in value but not in awareness, therefore the shadow cost is not decreased, allowing a purely temporary decrease in price. The paper also mentioned the possibility that returns drive awareness instead of the opposite. Denis et al (2003) face the same issue without bringing any answer to it.

Chen et al. (2004) go even further by comparing their deletion results with Lynch and Mendenhall (1997), whose evidence was interpreted as consistent with the downward-sloping demand curve hypothesis. Chen et al. show that the short-run results are similar: deleted firms lose about -14.44% from the announcement date to 10 days after the effective date. Nevertheless, when the event window is extended, the cumulative abnormal return 60 days after the effective date is only -6.32% and is not statistically significant. They therefore argue that the deletion evidence does not contradict the investor recognition hypothesis, which predicts a weaker permanent negative effect for deletion.

Building on their earlier work, Chen et al. (2019) provide a more recent analysis of changes in the MSCI Standard index. Their analysis covers 38 countries and demonstrates that additions to the index have a persistent, significantly positive abnormal return lasting up to 60 days after the effective date. By contrast, deletion exhibit a strong reversal effect, with prices returning to their pre-announcement level within the 60-day window. These findings are therefore consistent with the investor recognition hypothesis. Additionally, Elliot et al. (2006) offer a cross-analysis of all hypotheses mentioned in this paper and find evidence that abnormal returns due to a change in the index can be explained only by an increase in investor awareness.

By contrast, a competing strand of the literature reports a permanent price decline for deleted stocks. Kappou et al. (2008), in particular, emphasize that their evidence is inconsistent with the investor recognition hypothesis, since deleted stocks experience a substantial and permanent fall in price rather than the limited and asymmetric effect predicted by that hypothesis.

2.6 Liquidity Cost Hypothesis (LCH)

Although the liquidity analysis is not part of this paper because of limited access to the data, it is still very important to mention the hypothesis that arises from liquidity analysis. DEL In the context of the liquidity cost hypothesis, liquidity refers to the ability to rapidly execute sizable securities transactions at a low cost and with a limited price impact" (IMF, p.50)

Mikkelson & Partch (1985) studied the price effect of secondary distribution. However, the analysis differs from the previous study, Scholes (1972), by providing additional explanations about the origin of the price decrease when a large volume of shares is issued on a market. According to the authors, the price decline is significant only at the public disclosure and is due mainly to different costs. While Scholes (1972) already acknowledges the existence of transaction costs, Mikkelson & Partch go further by defining transaction costs more broadly to include the underwriting spread, the difference between the offering price and the closing market price on the sale date and other seller-incurred expenses. The underwriting spread is the biggest cost component and refers to the gap between what investors pay for the shares and what the seller actually receives net of the underwriter's compensation. For instance, an underwriter can be an investment banking group or broker-dealer syndicate such as J.P. Morgan, Goldman Sachs or Merril Lynch. While no evidence of temporary price change with recovery was found, the liquidity cost is still present through these underwriting spreads, which, according to them, increase with the relative size of the offering. The starting point of LCH is therefore Mikkelson and Partch's discoveries, which suggest that liquidity costs matter in secondary distribution, but that they are mainly driven by underwriting spread costs. Although index-rebalancing event studies do not involve an underwriter and therefore no underwriting spreads, their paper remains relevant because it shows that large transactions are not absorbed by the market without any compensation. During rebalancing, institutional investors and index tracking funds need to buy or sell large amounts of stock on a short horizon. Therefore, in the context of index rebalancing, the liquidity cost is not caused by an underwriting spread but by the price concession required to attract other market participants to supply liquidity and absorb the resulting order imbalance.

These results are similar to those of Amihud & Mendelson (1986), who conclude that liquidity matters for asset pricing. Their study is especially relevant because it focuses directly on the bid-ask spread and its relation to market returns. They conclude that a larger bid-ask spread not only represents higher transaction costs and lower liquidity; it also reflects the risk borne by market makers, which indicates a more volatile price. Although the risk factor is not the primary emphasis in the article. Also, their model explains that investors differ in expected holding periods; investors with short (long) horizons prefer low (high) bid- ask spread. This effect implies that the expected market return is an increasing and concave function of the spread. It increases because of compensation for illiquidity, but goes down because the stock is increasingly held by long-horizon investors who require less compensation for illiquidity. Apart from the shape of the function, the major findings of their empirical findings are that higher spreads require more returns; therefore, companies have a high incentive to improve the liquidity of their shares.

Amihud & Mendelson (1986) established the main intuition behind the LCH: When an asset is costly to trade (wide bid-ask spread), investors do not value it highly. The investor expects to lose part of the asset payoff when entering or exiting the trade, so the asset must compensate the investors through a lower price, which implies higher expected returns. Inversely, if an asset becomes more liquid, the expected return falls, and its price rises. This intuition, also called the liquidity-wealth-effect hypothesis, is the cornerstone of the LCH in rebalancing events.

Using this hypothesis, Hedge & McDermott (2003) ask the crucial question of whether being added or deleted from the S&P500 changes a stock's liquidity and if this shift will affect its price. The paper informs that liquidity sustainably improves (lower bid-ask spread) after the stock is added. An increase in trading volume and trade frequency is also noticeable and is the logical follow-up of a bid-ask spread decrease. This improvement in liquidity is interpreted as a decline in the direct cost of trading and, to a smaller proportion, as a decline in asymmetric information. The authors also find that an increase in liquidity is closely related to positive abnormal returns for the addition. On the contrary, deleted stocks experience negative abnormal returns and a wider bid-ask spread. Finally, their liquidity variable is statistically significant but explains the change in share price partially: "the observed decrease in trading costs can explain only a fraction of the observed abnormal return from an economic standpoint" (Hedge & McDermott, 2003, p. 449). Since the price effect for addition lasts two weeks, it emphasizes the imperfect substitution hypothesis as the main explanatory model according to their result, showing once again that most of the empirical studies cannot exclusively be explained by one hypothesis. Erwin and Miller (1998) report results that are broadly consistent with those of Hedge & McDermott (2003) but only for the subsample of non-optioned stocks. Their analysis is more restrictive and differs in methodology. First, they focus exclusively on index additions. Second, they distinguish between non-optioned stock and optioned stock, showing that the liquidity effect appears only for the former subsample. For non-optioned stocks, S&P500 inclusion is associated with a decline in bid-ask spreads, a permanent price increase and higher trading volume; by contrast, for optioned stocks, they find no significant reduction in spreads and interpret the price effect as temporary. The interpretation also differs between papers. Whereas informational effects are present but secondary in Hedge & McDermott, they are central in this study. Specifically, Erwin and Miller argue that the addition of a stock in the S&P500 increases informational efficiency mainly through arbitrage trading between the stock and the index derivatives, especially futures and options. Arbitrageurs compare prices across related markets and exploit temporary gaps until prices converge. This process brings new information to one market from the other so that both stock and derivative prices more closely reflect the stock's fundamental value. As prices become more informative, information asymmetry and market maker uncertainty decline, which in turn reduces the bid-ask spread and helps explain the abnormal returns observed for added non-optioned stocks.

While methodology and interpretation might differ, the literature agrees that the Liquidity Cost hypothesis helps explain why index rebalancing events might affect the stock prices. If inclusion improves liquidity, the investor faces a lower trading cost, which can increase the stock price. Also, the studies reviewed in this section show that liquidity is only one part of the story.

2.7 The disappearing effect

The disappearing index effect is a relatively recent phenomenon, already identified by Cusick (2002). Following the approach Beneish and Whaley (1996) and Lynch and Mendenhall (1997), Cusick studies the S&P 500 index effect after the 1989 policy change, which introduced a one-week interval between the announcement and the implementation of index revisions. Cusick's main contribution is to emphasize that the index effect became progressively less exploitable over time. He argues that although indexing activity continued to rise, investor awareness of arbitrage opportunities also increased, causing a larger share of the price adjustment to occur overnight immediately after the announcement. His interpretation is that markets became more efficient during the 1990s.

This phenomenon was documented again several years later. Kappou (2018) also observes a diminishing index effect and provides an empirical analysis focused exclusively on the more recent 2002-2013 period. For the full sample, the main findings show an abnormal return of 3.01% on the day following the announcement, with most of this movement occurring overnight, before any meaningful arbitrage can take place. By contrast, the abnormal return on the effective date is only 0.53%. This suggests that the "S&P game" explanation, proposed by Beneish and Whaley (1996), no longer holds in the same way.

The study also compares the pre- and post-2008 periods. This separation is meaningful because it captures the effects of the subprime crisis. Kappou argues that the diminishing effect is most likely linked to this crisis. After 2008, the cumulative abnormal return from AD+2 to AD+7 becomes negative and insignificant, whereas in the pre-crisis period, cumulative abnormal returns were significant and displayed clear signs of price pressure. The explanations proposed are largely interpretive rather than directly established through empirical testing. According to Kappou, the crisis triggered substantial changes in the market structure: improved algorithmic execution, more efficient direct market access for passive investors, stricter regulation, and tighter constraints on banks' ability to take large balance sheet positions. Taken together, these developments appear to have reduced the magnitude of the index effect. In this sense, Kappou extends Cusick's analysis by providing a more detailed examination of overnight and intraday price adjustment around S&P 500 index changes in a later period.

The most recent and comprehensive study on the subject is Greenwood & Sammon (2023). Their paper attempts to identify the underlying causes of the disappearing effect. The authors begin from a striking observation: "the price impact of being added to the S&P 500 has fallen dramatically, from 7.4% in the 1990s to only 0.3% over the past decade, with a similar decline for deleted stocks. This is puzzling because it occurred during a period of rapid growth in passive indexing. It is even more surprising given that earlier literature from the 1980s, such as Shleifer (1986) or Harris & Gurrel (1986), documented strong positive index effects.

To shed light on this phenomenon, Greenwood and Sammon test four explanations. The first is that characteristics of firms added to or deleted from the index may have changed over time. Newly added companies may now be more liquid, smaller relative to the index, easier to arbitrage, or already widely covered by analysts. To control for these factors, the authors estimate a regression in which the dependent variable is cumulative abnormal return. The explanatory variables include changes in arbitrage risk following Wurgler and Zhuravskaya (WZ), turnover as a proxy for liquidity, firm size, analyst coverage, and period dummy variables distinguishing the 1990s, 2000s, and 2010s.

The intuition behind these variables is straightforward. Size should matter because adding a larger firm requires index investors to purchase a greater quantity of shares to replicate the index, generating a larger demand shock and potentially a larger price effect. Arbitrage risk matters because, as Wurgler & Zhuravskaya (2002) argue, when a stock has close substitutes, arbitrageurs can trade against demand more easily, thereby reducing price pressure. Analyst coverage is included because joining the S&P 500 used to substantially increase a firm's visibility, whereas in more recent periods, firms entering the index are often already extensively followed, which limits any additional attention effect. Turnover serves as a proxy for liquidity: if a stock already has high turnover, its addition to or deletion from the index should represent a smaller shock, leading to lower price pressure.

In the end, controlling for these variables does little to explain the long-run decline in the index effect. The drop from the 1990s to the 2010s remains large and significant: about 6.6 percentage points (p.p.) without controls and 5.6 p.p. with controls. Although turnover and analyst coverage are insignificant, the authors do find that larger additions tend to generate larger inclusion effects. More precisely, a stock that is 1% larger relative to total S&P 500 capitalization is estimated to have an inclusion effect that is about 18% larger. However, this factor explains only about 50 basis points of the overall decline. They illustrate the importance of size with Tesla's inclusion in 2020, which was unusually large and produced a cumulative abnormal return of 5.2% at announcement and 4.5% at implementation. Nevertheless, even after controlling for firm characteristics, the downward trend remains highly significant.

The second explanation concerns firms that migrate from another S&P index, such as the S&P Mid-Cap index, into the S&P 500. In such cases, S&P 500 funds buy the stock, but Mid-Cap index funds simultaneously sell it. The net demand shock is therefore much smaller than gross purchases alone would suggest. Greenwood & Sammon show that this migration effect has become far more common over time: in the 1990s, 69% of additions and less than 10% of deletions involved migration, whereas in recent years both figures exceed 70%. When they compare abnormal returns, they find a clear pattern: from the late 1990s to the 2010s, abnormal returns for direct additions declined by 4.8%, while abnormal returns for migration additions declined by 8.5%. One of the paper's main conclusions is therefore that net demand shocks have fallen because index changes increasingly involve transfers between related indices rather than entirely new additions or deletions.

The third explanation is that index changes may have become more predictable. If so, arbitrageurs can buy or sell the relevant stocks in advance, meaning that part of the price effect occurs before the official announcement. To test this, the authors examine a pre-announcement window covering the 100 days before the announcement date. They find that cumulative abnormal returns increased from 9.7% in the 1990s to 18.7% in the 2010s. Cumulative abnormal returns up to ten days after announcement also increased, but in a smaller proportion. However, in the short window immediately preceding the announcement, evidence of front-running is much weaker. The authors therefore conclude that predictability may explain part of the decline in the index effect, but not all of it.

The fourth and final explanation concerns the increase in market liquidity. In the paper, price impact is expressed as the product of the demand shock and a market market-multiplier, M. If price pressure disappears while demand remains high, then M must have declined. Their results indicate that M fell by a factor of about 20 for additions and even more for deletions, suggesting that markets have become much better able to absorb index-related trading. However, as with the previous explanations, improved liquidity is only part of the story, because the timing of the broader increase in market liquidity does not fully coincide with the disappearance of the index effect.

Overall, after testing these four theories, two stand out most clearly: the migrating explanation and the improvement in liquidity. Both produce significant results and provide compelling evidence as to why the index effect may have weakened over time. The broader conclusion is that, as Greenwood and Sammon

(2023, p. 31) argue, “when a demand shock becomes regular and repeated, competitive markets adapt over time to minimize price impact, (…)”.

The disappearing effect is highly relevant for the present paper, since the analysis is conducted on a recent year, 2025, and may therefore be directly affected by this phenomenon.

2.8 Morgan Stanley Capital International (MSCI)

2.8.1 History of the MSCI

Morgan Stanley Capital International (MSCI) is widely recognized as an index provider, although its operations extend beyond index construction to encompass financial data services, risk analytics, ESG and sustainability research, and private-asset solutions. Given the scope of this paper, the analysis is confined to MSCI’s core business, namely index construction. (MSCI, 2026a)

The international indices (except the U.S.) were initially developed by Capital International. In 1986, Morgan Stanley acquired the rights to these indices, giving rise to Morgan Stanley Capital International. Throughout the 1980s, MSCI indices served as the primary benchmark for non-U.S. equity markets before facing competition from other providers such as FTSE, S&P, and Citibank. In 2007, Morgan Stanley announced its decision to divest MSCI, and the separation was finalized in 2009. (Wikipedia, 2026; SEC, 2009)

Today, MSCI is widely regarded as a global leader in equity indexing. According to the official MSCI website (2026a), approximately $18.3 trillion in Asset Under Management (AUM) is benchmarked to MSCI equity indexes, more than 246,000 equity indexes are calculated globally, and around $2 trillion in equity ETF AUM is linked to MSCI indexes. MSCI constructs its indexes in accordance with the Global Investable Market Index (GIMI) methodology.

The GIMI methodology serves as a comprehensive global framework with several key objectives. First, it seeks to maximize the coverage of investable equities. Second, it classifies securities consistently across countries by market capitalization into large-, mid-, and small-cap segments. Third, it places strong emphasis on investability and replicability through size classification and liquidity screening. Fourth, it aims to preserve index stability while remaining sufficiently responsive to market developments. Fifth, it establishes minimum free-float requirements for index eligibility and relies on free-float-adjusted market capitalization weighting to better reflect the size of each investment opportunity. Finally, it ensures the timely and consistent treatment of corporate events and synchronized rebalancing across global markets. (MSCI, 2026b)

2.8.2 MSCI indexes construction

To construct MSCI global investable market Indexes, the methodology follows six main steps. First, MSCI defines the equity Universe for each market by identifying eligible equity securities and assigning them to the appropriate country. Second, it determines the market investable equity universe by applying investability screens to each company and security within a given market. Third, MSCI defines the market capitalization size segments for each market. These consist of five segments: the Investable Market Index (large-, mid-, and small-cap), Standard index (large- and mid-cap), the Large Cap index, the Mid Cap index, Small Cap index. Fourth, MSCI applies index continuity rules for the Standard Index in order to ensure a minimum level of representation within each national market. In particular, a standard index must contain at least five stocks in developed markets and at least three stocks in emerging markets. Finally, once securities have been classified by size, MSCI organizes them into broader index groupings. After being allocated to their respective size segments, stocks can be aggregated according to market classification (Developed, Emerging or frontier market), geographic area, economic characteristics, or other criteria, to form composite indexes such as the MSCI World Index, the MSCI Emerging Markets Index, or regional indexes such as the MSCI North America Index. Although MSCI also places considerable emphasis on its GICS-based indexes, these fall outside of the scope of the present research. (MSCI, 2026b)

2.8.3 MSCI Index reconstitution policy

The MSCI Global Investable Market Indexes are updated regularly to reflect changes in equity markets and market segments in a timely manner. At the same time, MSCI aims to preserve "index continuity, continuous investability of constituents and replicability of the indexes, and Index stability and low index turnover" (MSCI, p.35). In other words, equity markets constantly evolve through mergers, share issuance, free float and especially market capitalization. If an index were not periodically reconstituted, it would no longer accurately represent the market it is designed to track. This would weaken the replicability emphasized by MSCI and could generate tracking errors for funds and ETFs that follow the index. Therefore, index reconstitution is necessary to maintain market representativeness while balancing stability and turnover costs.

To achieve this objective, MSCI maintains its indexes through two main mechanisms. First, it conducts quarterly index reviews in February, May, August and November. Second, it implements ongoing event-related changes, which are generally incorporated as soon as they occur. It should also be noted that certain newly listed companies, particularly those associated with sufficiently large initial public offerings (IPOs), may be included before the next quarterly review; in general, such securities are added at the close of the tenth day of trading. Ongoing event-related changes are excluded from the present study because their nature and timing are generally not suitable for a proper event-study analysis. (MSCI, 2026b)

With regard to the announcement policy, the results of index changes are disclosed at least two weeks before their effective implementation dates. Under the quarterly review system, these changes are, in most cases, implemented on the last trading day of the relevant month. (MSCI, 2026b)

2.8.4 MSCI World Small Cap ex USA Index

The MSCI World Small Cap ex USA index is central to the study. It captures the small-cap segment across 22 of the 23 developed markets by excluding the United States. More specifically, the 22 countries included are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland and the United Kingdom. The index comprises 2,218 constituents and covers approximately 14% of the free-float-adjusted market capitalization of each country.

This 14% coverage reflects MSCI's broader methodology for dividing each equity market into size segment. One particular feature of this index is therefore its focus on small-capitalization companies. As mentioned earlier, MSCI classifies equity markets into several segments: the Investable Market Index (IMI), which includes large-, mid-, and small-cap stocks, the Standard Index, which includes large- and mid-cap stocks; and the separate Large Cap index, Mid Cap index, Small Cap indexes.

In the MSCI methodology, small-cap stocks are identified as the securities included in the Investable Market Index but excluded from the Standard Index. In other words, the Small Cap Index is derived from the difference between the IMI and the Standard Index. To define these size segments, MSCI applies thresholds based on each market's free-float adjusted market capitalization. The Standard Index targets approximately the largest 85% +- 5% of each market's free-float-adjusted capitalization, meanwhile, the Investable Market Index extends the coverage to approximately 99% +1% or -0.5% of the markets' free-float-adjusted capitalization. Therefore, the difference between these two coverage levels corresponds to the small-cap segment, which explains why the MSCI World Small Cap ex USA Index covers approximately 14% of each country's free-float-adjusted market capitalization. (MSCI, 2026b)

3. Data Sample

3.1 MSCI Data

One of the initial objectives of the study was to complement the analysis of the MSCI Small Cap world ex-USA Index with a country-level analysis that could help explain cross-country differences in index effects. Chen et al. (2019) already provide a comparable cross-country analysis, although their sample differs in terms of market capitalization coverage and methodology. Nevertheless, their study remains one of the main sources of inspiration for the present paper. Accordingly, the sampling procedure adopted here is broadly similar.

To begin, we collect the reconstitution lists for each quarterly review. These lists are publicly available and report constituent changes across the broader MSCI Global Small Cap Indexes. The MSCI Global Small Cap Indexes represent the small-cap segment of MSCI's global equity universe and are disaggregated by country and region. Because the MSCI Global Investable Market Indexes methodology states that indexes are constructed at the individual market level, these reconstitution lists can be used to identify constituent changes relevant to the MSCI World Small Cap ex-USA index. Since the study covers the year 2025, four reconstitution lists are examined, corresponding to the February, May, August and November quarterly reviews. Figure 1 presents the number of constituent changes in each country for each review month, distinguishing between additions and deletions.

Figure 1: MSCI quarterly review composition changes

	February		May		August		November	
Country	Add	Del	Add	Del	Add	Del	Add	Del
Australia	11	9	9	7	6	2	11	3
Austria	0	1	0	0	1	6	1	2
Belgium	2	1	0	1	1	0	1	1
Denmark	1	1	1	1	0	0	0	0
Finland	0	1	0	0	0	0	0	0
France	1	3	1	0	2	0	8	0

Germany	3	3	3	1	1	3	0	4
Hong Kong	5	1	2	2	2	0	7	2
Ireland	0	0	0	0	0	0	0	0
Israel	1	2	3	0	5	3	6	0
Italy	2	2	2	0	1	0	2	1
Japan	14	36	6	5	11	2	3	19
Netherlands	0	0	0	0	1	0	0	1
New Zealand	1	1	0	0	0	0	0	0
Norway	1	3	1	1	2	2	0	0
Portugal	0	0	0	0	0	1	0	0
Singapore	0	0	1	2	2	0	5	1
Spain	0	2	0	0	0	2	2	0
Sweden	1	2	4	1	9	0	3	5
Switzerland	4	2	0	0	2	2	3	5
United Kingdom	9	18	2	2	7	6	4	9

Data are from MSCI Inc. (2025a, 2025b, 2025c, 2025d).

To obtain the daily total returns for all constituent changes reported in Figure 1, we used LSEG Datastream through its Excel extension. More specifically, the analysis relies on the Datastream for Office (DFO) Request table, which can retrieve the required data from the Datastream database using the International Securities Identification Number (ISIN). However, the reconstitution lists provided by MSCI do not include the ISINs. The ISINs of firms added to or deleted from the index were therefore retrieved from Bloomberg[3]. The Python code presented in Appendix A was designed to match, as closely as possible, the company names reported in the MSCI reconstitution lists with those contained in the Bloomberg file, in order to assign the correct ISIN to each added or deleted firm. This matching procedure is subject to certain limitations and leads to a modest reduction in the

[3] The file was provided by the company AG Insurance

final sample size, which could potentially have been reduced through access to a premium version of LSEG Datastream.

The sample is then filtered according to several criteria:

The first criterion relates to the two types of index reconstitution, previously mentioned, provided by MSCI: Regular quarterly reviews and irregular changes referred to as ongoing event-related changes. The latter are generally associated with corporate events such as mergers and acquisitions, new equity issues, or bankruptcies. These changes are excluded in order to avoid misinterpretation or contamination effects arising from major corporate events. The underlying assumption is that market participants are already aware when a firm is undergoing such an event. (Lynch & Mendenhall, 1997)

This exclusion also helps mitigate survivorship bias, defined as "a logical error in which attention is paid only to those entities that have passed through (or survived) a selective filter, which often leads to incorrect conclusions" (Eldridge, 2024). In the context of index-effect studies, such bias may arise when a firm's addition to or deletion from an index is conditional on shareholder approval of a restructuring plan, such as a merger or spin-off. If approval is more likely following a favorable stock-price reaction, the final sample may disproportionately include firms with positive returns, thereby biasing the estimated effect of index inclusion or exclusion. (Lynch & Mendenhall, 1997)

The second criterion concerns the exclusion of the American regions. Although both the United States and Canada are part of the broader MSCI World Small Cap Index, the present study focuses on the MSCI World Small Cap ex USA Index. In addition, 26 additions and 22 deletions involving Canadian firms are excluded. These observations are removed because, at the time MSCI announces index changes, some of the American markets may still be open, whereas European and Asian markets may be closed. As also noted by Chen et al. (2019), this timing difference may hinder the accurate measurement of the information effect at the announcement. A further justification for excluding the American region, and especially the United States, lies in the vast body of existing research on the S&P

500, which reduces the incremental contribution of conducting a similar analysis for the U.S. market in this study.

The third criterion is purely data-driven and follows Chen et al. (2019). Firms must have at least 30 days of daily return data during the period preceding the announcement date and at least 30 days during the period following the effective date.

Finally, to improve the quality of the cross-country analysis, we retain only firms whose ISIN corresponds to the country to which MSCI assigns them in the rebalancing list. This discrepancy arises because some firms have a different country of incorporation, country of domicile or country of risk in the Bloomberg Database than in the MSCI classification. The issue is particularly pronounced for Hong Kong, with the result that a large number of additions and deletions in that market are excluded from the analysis. Applying this criterion makes it possible to construct a cleaner database, especially for future research using geographical variables.

Overall, these selection criteria, together with the limited data loss resulting from ISIN, reduce the sample from 393 observations (see Figure 1) to 333 observations, of which 128 occur in February, 90 in November, 68 in August, and 47 in May. In this study, one observation corresponds to a single stock added or deleted from the MSCI World Small-Cap ex U.S. Index

3.2 Factors Data

Because the empirical model presented later in the paper relies on the Carhart four-factor specification, this section briefly describes the data source and construction of the factors used in the analysis. The factors were obtained from the database maintained by Kenneth R. French[4]. More specifically, we use the daily Fama-French three factors and the daily momentum factor for developed markets excluding the United States. This choice provides the closest match to the MSCI

[4] Available on the website:
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

World Small Cap ex-U.S. Index, since both refer to developed equity markets outside the United States. The Carhart four-factor model includes the market factor, the size factor, the value factor and the momentum factor. The market factor is defined as the excess return on the value-weight market portfolio:

$$R_{m,t} - R_{f,t}$$

Where $R_{m,t}$ is the return on the developed ex-U.S. market portfolio and $R_{f,t}$ is the U.S. one-month T-bill rate.

The size and factors are SMB and HML. SMB or Small Minus Big, captures the return difference between small-cap stock and large-cap stocks. HML, or High Minus Low, captures the return difference between value stocks and growth stocks. In the Fama-French developed ex-U.S. dataset, SMB and HML are constructed from six value-weighted portfolios formed using independent sorts on size and book-to-market equity.

At the end of each June, stocks are sorted into two size groups, Small and Big. Small stocks are those in the bottom 10% of regional market capitalization, while big stocks are those in the top 90%. For book-to-market, stocks are divided into three groups Growth, Neutral and Value groups using the 30^{th} and 70^{th} percentiles of book-to-market equity in each region. The 6 portfolios are therefore a combination of these classifications: Small Growth (SG), Small Neutral (SN), Small Value (SV), Big growth (BG), Big Neutral (BN), Big Value (BV). The SMB and HML are calculated as the average return on the three small-stock portfolios minus the average return on the three big-stock portfolios:

$$SMB_t = \frac{1}{3}\left(R_{SG,t} + R_{SN,t} + R_{SV,t}\right) - \frac{1}{3}\left(R_{BG,t} + R_{BN,t} + R_{BV,t}\right)$$

HML is calculated as the average return on the three value portfolios minus the average return on the three growth portfolios:

$$HML_t = \frac{1}{2}\left(R_{SV,t} + R_{BV,t}\right) - \frac{1}{2}\left(R_{SG,t} + R_{BG,t}\right)$$

The fourth factor is the momentum factor, WML, which stands for Winners Minus Losers. This factor controls for the tendency of stocks that performed well in the recent past to continue outperforming, and stocks that performed poorly to continue underperforming. Momentum is measured using each stock's cumulative return from day *t-250* to *t-20*, excluding the most recent trading month. Based on this measurement, stocks are classified as Losers, Neutral, or Winners. Combined with the size classification, this produces six value-weighted portfolios: Small Losers (SL), Small Neutral (SN), Small Winners (SW), Big Losers (BL), Big Neutral (BN), Big Winners (BW). The Momentum factor is therefore calculated as the average return on the winner portfolios minus the average return on the loser portfolios:

$$WML_t = \frac{1}{2}\left(R_{SW,t} + R_{BW,t}\right) - \frac{1}{2}\left(R_{SL,t} + R_{BL,t}\right)$$

Finally, all factor returns are expressed in U.S. dollars rather than local currency. Accordingly, the daily total return data used in our empirical analysis are also denominated in U.S. dollars in order to ensure consistency with the Carhart four-factor model.

4. Methodology

4.1 Input modification

To begin the analysis, it is necessary to compute the daily total return of each stock. Following Chakrabarti et al. (2005), the raw input used in our sample is the return index, obtained from Datastream and constructed under the assumption that dividends are reinvested. The Datastream for office (DFO) request table describes the computation of the return index (RI). Specifically, the RI measures the growth in value of a security over a given period. It is therefore a cumulative index, typically initialized at a base value of 100. The return index is computed as follows:

$$RI_t = RI_{t-1} \times \frac{P_t}{P_{t-1}} \times \left(1 + \frac{DY_t}{100} \times \frac{1}{N}\right) \tag{1}$$

Where RI_{t-1} denotes the cumulative wealth up to day $t-1$. This quantity is multiplied by the price-return factor $\frac{P_t}{P_{t-1}}$ which captures the change in the stock price between day $t-1$ and day t. It is then multiplied by the dividend-accrual factor, which represents the daily contribution of dividends and where N is the frequency used to convert annual dividend yield into a return for one period. Because the return index is a cumulative wealth index rather than a one-day performance measure, it incorporates the entire return history of the security up to date t . For example, if the base value is set to 100, the index may rise to 110 after several days; however, this value does not by itself represent a daily return. Instead, it indicates that the value of the investment has increased by 10% relative to the base date. Consequently, in order to obtain the daily total return, it is necessary to compute the one-day variation in the return index, as shown in Equation (2).

$$r_t^{TR} = \frac{RI_t}{RI_{t-1}} - 1 \tag{2}$$

4.2 Event Study

The empirical analysis follows the standard event-study framework. Event study methodology is appropriate for investigating abnormal returns and is widely used in the literature on index reconstitutions and related market events (MacKinlay, 1997; Chakrabarti et al., 2005; Greenwood and Sammon, 2023). MacKinlay (1997) provides a framework for conducting a proper event study in the context of abnormal returns produced by index changes and defines it as a method of measuring the impact of a specific event on the value of a firm. The first step consists of defining three main windows: the estimation window, the event window and the post-event window.

The estimation window corresponds to the interval [AD-250, AD-30]. There is no strict rule regarding its exact length. The choice reflects a common trade-off in event studies: longer estimation windows generally yield more precise parameter estimates, whereas shorter windows reduce the risk of event contamination (Armitage, 1995). Armitage (1995) notes that most daily event studies employ estimation windows of approximately 100 to 300 trading days. The same author also discusses Corrado and Zivney (1992), who compare the performance of three statistical tests using estimation windows of 239, 89 and 39 trading days, and show that the deterioration in performance remains limited, with the exception of the shortest window, which slightly deteriorates. On this basis, Armitage (1995) concludes that an estimation period of at least 100 days is generally considered acceptable. The upper bond of the estimation window must also be set sufficiently before the event window. MacKinlay (1997) argues that the estimation window and the event window should not overlap, since returns around the event may bias the parameters estimated over the estimation period. For this reason, a buffer zone between the two windows is commonly adopted in the event study literature.

Taking these considerations into account, we follow a specification close to that of MacKinlay (1997) by choosing a lower bound of 250 trading days before the announcement date. This choice satisfies the minimum length commonly recommended in the literature. In addition, we adopt a 30-days buffer zone between the estimation window and the event window, which is slightly more conservative than the conventional specification. The estimation window therefore contains 221 trading days, with both endpoints included.

The event window and post-event window follow the specification used by Chen et al. (2019), one of the most recent and prominent studies on MSCI index rebalancing events. This choice can be justified on two grounds. First, it ensures greater methodological consistency within this relatively narrow field of research and facilitates comparison across studies, despite differences in model specification. Second, Chen et al. (2019) document a reversal toward pre-adjustment levels for the negative abnormal returns associated with deletions within 60 days after the effective date. The temporary nature of this reversal is central to assessing the validity of the investor recognition hypothesis. All main windows are illustrated in Figure 2.

It should be noted that the event window is technically a pre-implementation window, defined as [AD, ED-1], and therefore excludes the effective date itself. However, the effective date is still analyzed separately over the interval [ED-2, ED+2], while the announcement period is examined over [AD-2, AD+2], as both dates are central to understanding the formation of abnormal returns. The main post-event window [ED, ED+60] and the event window combined are further divided into three cumulative windows in order to identify more precisely the timing of any reversal in abnormal returns: [AD, ED+20], [AD, ED+20], and [AD, ED+60] (see Figure 3).

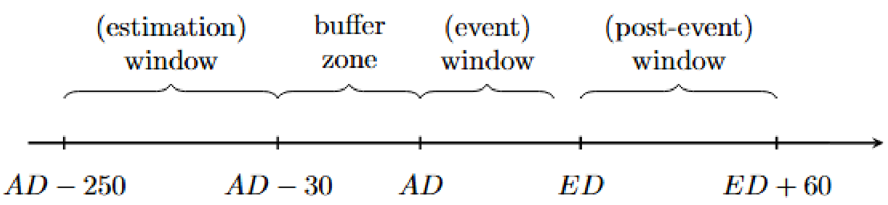

Figure 2: Main windows of Event study

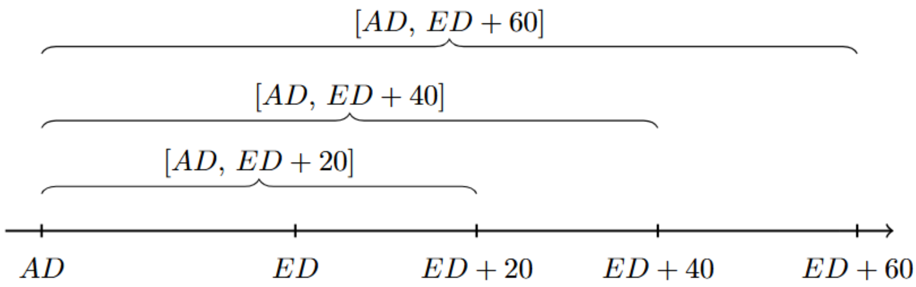

Figure 3: Post sub-event windows

To end this section, Figure 4 illustrates the different windows applied to our four 2025 reviews used in our analysis.

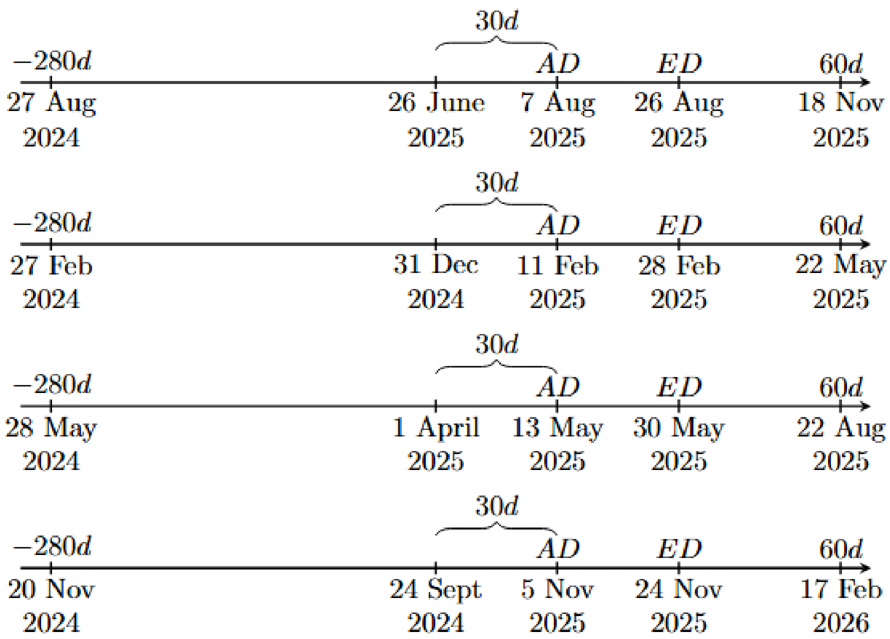

Figure 4: Event study according to the sample

The remaining steps of MacKinlay framework concern the specification of the model itself, which is presented in the following section.

4.3 Model description

4.3.1 Capital Asset Pricing Model Fama-French three-factor model

The capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Litner (1965), explains the expected excess return of a stock by its exposure to the excess return on the market portfolio. In its regression form, the CAPM model is:

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{Mt} - R_{ft}\right) + \varepsilon_{it}$$

In this framework, market beta captures the only source of risk that should be priced in expected returns. A stock with a higher beta is expected to yield a higher return because it is more exposed to market-wide fluctuations, whereas firm-specific risk can be diversified away and should therefore not command a risk premium. Under the CAPM, differences in expected returns should only be explained by differences in their sensitivity to the market portfolio.

However, this view was challenged by Fama & French (1992, 1993 and 1996) who questioned the ability of the CAPM model to explain average stock returns. In particular, Fama & French (1992) show that the market beta alone has little explanatory power for the cross-section of average returns, whereas other firm characteristics, such as size and book-to-market equity (BE/ME), play a much more important role. Book-to-market equity is defined as the ratio of book equity, that is, the accounting value of shareholders' equity, to market equity, which is obtained by multiplying the share price by the number of shares outstanding. Fama and French also examine leverage and the earnings-to-price ratio (E/P), but in multivariate regressions these variables display substantially weaker explanatory power, as their effect are largely subsumed by size and book-to-market equity. Their results indicate that small firms tend to earn higher average returns than large firms, and that firms with high book-to-market ratios tend to earn higher average returns than firms with low book-to-market ratios.

To improve the model and resolve this inefficiency to explain average return, Fama and French (1993) propose a multifactor model that augments the market factor with two[5] additional factors. The first factor, SMB (Small Minus Big), captures the size effect, while the second factor, HML (High Minus Low), captures the book-to-market effect. To construct these factors, stocks are independently sorted by size into two groups, Small (S) and Big (B), and by book-to-market equity into three groups High (H) Medium (M) and Low (L). These double sorts generate six different value-weighted portfolios: S/L, S/M, S/H, B/L, B/M, B/H.

SMB is defined as “the difference, each month, between the simple average of the returns on the three small-stock portfolios (S/L, S/M, and S/H) and the simple average of the returns on the three big-stock portfolios (B/L, B/M, and B/H)” (Fama & French, 1993, p. 9). HML is defined as the difference between the average return on the two high BE/ME portfolios (S/H and B/H) and the average return on the two low BE/ME portfolios (S/L and B/L). The resulting three-factor model (FF3) can be written as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{Mt} - R_{ft}) + s_i\, SMB_t + h_i\, HML_t + \varepsilon_{it}$$

Taken together, Fama & French (1992) challenge the CAPM by showing that size and book-to-market are more informative than beta in explaining average stock returns, while Fama and French (1993) incorporate these empirical regularities into the FF3 model. Fama and French (1996) further show that FF3 is able to explain most previously documented return anomalies. However, it fails to account for the short-term return documented by Jegadeesh and Titman (1993). This empirical limitation was later addressed through the introduction of the momentum factor in Carhart’s four-factor model.

4.3.2 Carhart four-factor model

The Carhart four-factor model presented by Carhart (1997), addresses whether mutual funds that performed well in the past continue to outperform because of persistent managerial ability, as suggested by the “hot hands” hypothesis of Hendricks et al (1993, as cited in Carhart, 1997). Carhart’s shows that this persistence is not primarily attributable to managerial skill but is largely explained

[5] To be accurate Fama & French (1993) introduced two additional bond factor TERM and DEF for which is outside the scope of our study

by exposure to common return factors, particularly momentum, as well as by differences in expenses and transaction cost. The model extends the Fama-French three-factor model by adding a momentum factor. Formally, the model is specified as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}MOM_t + \varepsilon_{i,t}$$

Where $R_{i,t}$ is the return of security I, $R_{f,t}$ is the risk-free rate, $R_{m,t} - R_{f,t}$ is the market excess return, SMB_t captures the size effect, HML_t captures the value effect, and MOM_t (or sometimes WML) captures the momentum effect. The intercept represents the abnormal return after controlling for common risk.

Carhart (1997) also highlights the limitations of the FF3 model by comparing its pricing error with those of the four-factor specification. He demonstrates that pricing errors decline once the momentum factor is incorporated into the model. More specifically, the mean absolute pricing error falls from 0.35% per month in CAPM to 0.31% in the FF3 model to finally 0.14% in the four-factor model.

4.4 Justification of the Model

The Market Model, whether adjusted or unadjusted, is widely used in the rebalancing index literature (Harris & Gurel, 1986; Shleifer, 1986; Beneish and Whaley, 1996; Lynch and Mendenhall, 1997; Chen et al., 2004; Chen & al., 2019). This naturally raises the question of why the present study relies instead on the Carhart four-factor model.

One reason for the widespread use of the Market model is its limited data requirement. In particular, the adjusted market model can be implemented even in the absence of pre-event estimation data. By contrast, the use of Fama-French three-factor model or the Carhart four-factor model is often constrained by the availability of factor data, while constructing such factors independently is considerably more demanding. In the present study, however, this limitation does not apply, as the required factor series and daily total return data for the estimation window were successfully retrieved.

A second reason lies in the methodological prominence of the market model in the event-study literature. MacKinlay (1997), whose contribution remains one of the most influential methodological references for event studies of index changes, notes that the restrictions imposed by the Capital Asset Pricing Model (CAPM) already mentioned in Fama and French (1992 & 1996), are questionable. "However, deviations from the CAPM have been discovered, implying that the validity of the restrictions imposed by the CAPM on the market model is questionable." (MacKinlay, p. 19). In his paper, MacKinlay briefly mentions that Eugene Fama and Kenneth French's (1996) study discusses the anomalies but omits to mention the results and conclusions of it. He then concluded that it will be easier to use the Market Model. Nevertheless, as previously mentioned, Eugene Fama & Kenneth French (1996) results conclude that these anomalies generated by the exclusion of certain firm characteristics such as size, earnings/price, cash flow/price, book-to-market equity, past sales growth, long-term past return, and short-term past return, mostly disappear in a three-factor model.

Most importantly, each additional Fama-French factor helps control for return variation attributable to firm characteristics rather than to the index event itself. This is especially relevant in the present study, which focuses on small-cap stocks. Unlike single-factor models such as market model, and even more so unlike the CAPM, the Fama-French three-factor model allows expected returns to vary with size and value characteristics. As Kappou et al. (2008) note, "The Fama-French model incorporates additional risk factors, giving a potentially more accurate picture of the long-run performance of firms following inclusion after allowing for the performance that would have been expected given their characteristics" (p. 24). Their empirical results support this argument by showing that long-run performance differs meaningfully across firms of different sizes. In particular, for the 1998-2002 period, the long-run performance of added firms varies substantially across size groups, while important differences are also observed in the earlier subperiod. These findings suggest that size-related effects may materially influence measured abnormal returns and therefore must be controlled for. In the context of the present study, this point is of particular importance: if size is omitted from the expected-return model, part of the estimated abnormal return may simply reflect the fact that the stock belongs to the small-cap segment rather than a genuine index effect.

Kappou et al. (2008) also highlight the potential value of controlling for momentum, as proposed by Carhart (1997). They do not include a momentum factor because, at the time of their study, momentum data were only available at the monthly frequency, which was not suitable for an analysis based on daily returns. This constraint no longer applies. The Kenneth R. French data library now provides a daily momentum factor, making it possible to incorporate momentum into the present analysis and thereby obtain a more comprehensive risk-adjusted assessment of the index effect. This addition is particularly relevant in the context of index rebalancing, because stocks being added to or deleted from an index often exhibit extreme recent return patterns. Inclusion and exclusion decisions are frequently associated with strong prior performance or underperformance over the preceding period. Controlling for momentum is therefore essential in order to distinguish the effect of the index event itself from pre-existing return continuation.

Despite these findings, the use of the Fama-French three-factor model, and even more so of the Carhart four-factor model, remains relatively uncommon in the index-rebalancing literature. In this respect, the present study makes a distinctive methodological contribution.

4.5 Application of the Model

Following the event-study framework of MacKinlay (1997), the factor specifications of Fama and French (1993) and Carhart (1997), and the contribution of Kappou et al. (2008), one of the few studies to employ the Fama-French three-factor model in the context of index effects, this section explains how abnormal returns are computed in the present study.

4.5.1 Normal returns

The underlying intuition is straightforward. In order to compute abnormal returns, the first step is to estimate each stock's factor loadings over the estimation window. To do so, we estimate the Carhart four-factor model for each stock i on day t, where t belongs to the estimation window:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}MOM_t + \varepsilon_{i,t}$$
$$\text{for } t \in [AD - 250,\ AD - 30]$$

In this regression, the dependent variable is the excess return on stock i at day t , defined as the difference between the stock return and the risk-free rate, $R_{i,t} - R_{f,t}$. The explanatory variables control respectively for overall market movements, the size effect, the value effect and the momentum effect. The intercept α_i captures the average excess return not explained by the four factors over the estimation window. The error term, $\varepsilon_{i,t}$ represents the idiosyncratic component of return on day t, that is, the portion of the stock's return that cannot be explained by the four systematic factors and is therefore specific to the individual stock. Estimating this regression yields the coefficients $\widehat{\beta_{MKT,\iota}}$, $\widehat{\beta_{SMB,\iota}}$, $\widehat{\beta_{HML,\iota}}$, $\widehat{\beta_{MOM,\iota}}$. These estimated coefficients measure the stock's normal exposure to the market, size, value, and momentum factors during the estimation window, that is, outside the event window. For each parameter, the null hypothesis is that the coefficient is equal to zero. For the intercept, it would mean that the stock does not earn a statistically significant average excess return after controlling for the four factors. For the factor coefficients, the null hypothesis implies that the stock has no exposure to the market for $\beta_{MKT,i}$, to the size factor $\beta_{SMB,i}$, to the value-growth factor $\widehat{\beta_{HML,\iota}}$ and to the momentum factor $\widehat{\beta_{MOM,\iota}}$. By contrast, rejecting the null hypothesis for a given coefficient indicates that the corresponding factor helps explain the stock's normal excess return during the estimation window.

The next step is to compute the expected normal returns for each day in the event window and in the post-event window. For each stock and each day in these windows, the expected excess return is calculated using the coefficients estimated over the pre-event estimation period and therefore reflects the return that would be expected in the absence of the event:

$$\left(\widehat{R_{i,t}^{N} - R_{f,t}}\right) = \widehat{\alpha_i} + \widehat{\beta_{MKT,i}}\left(R_{m,t} - R_{f,t}\right) + \widehat{\beta_{SMB,i}} SMB_t + \widehat{\beta_{HML,i}} HML_t + \widehat{\beta_{MOM,i}} MOM_t$$

To obtain the normal stock return:

$$\widehat{R_{i,t}^{N}} = R_{f,t} + \left(\widehat{R_{i,t}^{N} - R_{f,t}}\right)$$

Which gives:

$$\widehat{R_{i,t}^{N}} = R_{f,t} + \widehat{\alpha_i} + \widehat{\beta_{MKT,i}}\left(R_{m,t} - R_{f,t}\right) + \widehat{\beta_{SMB,i}} SMB_t + \widehat{\beta_{HML,i}} HML_t + \widehat{\beta_{MOM,i}} MOM_t$$

Where $\widehat{R_{i,t}^{N}}$ denotes the stock's expected normal raw return on day t and $\left(\widehat{R_{i,t}^{N} - R_{f,t}}\right)$ denotes its expected normal excess return.

4.6 Abnormal returns

This section elaborates on how abnormal returns were obtained, as well as the construction of average abnormal returns, cumulative abnormal returns, and cumulative average abnormal returns, which are central to the interpretation of the empirical results.

Abnormal returns are defined as the difference between the actual return observed for a stock and its estimated normal return:

$$AR_{i,t} = \left(R_{i,t} - R_{f,t}\right) - \left(\widehat{R_{i,t}^{N} - R_{f,t}}\right)$$

Or equivalently:

$$AR_{i,t} = R_{i,t} - \widehat{R_{i,t}^{N}}$$

Substituting the expected return from the Carhart four-factor model yields:

$$AR_{i,t} = R_{i,t} - \left[R_{f,t} + \widehat{\alpha_i} + \widehat{\beta_{MKT,i}}\left(R_{m,t} - R_{f,t}\right) + \widehat{\beta_{SMB,i}} SMB_t + \widehat{\beta_{HML,i}} HML_t + \widehat{\beta_{MOM,i}} MOM_t\right]$$

After computing the abnormal returns for each day t, we compute the average abnormal return (AAR) around key event dates, namely the announcement date and the effective date. Specifically, we use the windows [AD-2, AD+2] and [ED-2, ED+2]:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$$

where N denotes the number of firms included in the sample. The AAR_t therefore measures the average abnormal return observed across all firms on day t.

For the second part of the analysis, we compute the cumulative abnormal return for each stock *i* by summing daily abnormal returns over a given window $[\tau_1, \tau_2]$:

$$CAR_{i,[\tau_1,\tau_2]} = \sum_{t=\tau_1}^{\tau_2} AR_{i,t}$$

where τ_1 and τ_2 denotes the lower and upper bounds of the sub-event windows considered in our analysis, which are [AD, ED-1], [AD, ED+20], [AD, ED+40], and [AD, ED+60]. Therefore, τ_1 = AD, while $\tau_2 \in \{ED-1,\ ED+20,\ ED+40,\ ED+60\}$

The cumulative average abnormal return, ($CAAR_{T_0,T_1}$) over a given sub-event window $[\tau_1, \tau_2]$ is therefore obtained by averaging individual cumulative abnormal returns across all firms in the sample:

$$CAAR_{[\tau_1,\tau_2]} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,[\tau_1,\tau_2]}$$

In the empirical analysis, τ_1=AD, while $\tau_2 \in \{ED-1,\ ED+20,\ ED+40,\ ED+60\}$. Therefore, the CAAR is computed over the four sub-event windows: [AD, ED-1], [AD, ED+20], [AD, ED+40], and [AD, ED+60]

4.7 Statistical Testing

To assess whether average abnormal returns and cumulative average abnormal returns are statistically significant, a one-sample t-test is applied to the average abnormal returns. This approach is consistent with much of the recent literature on MSCI rebalancing events, including Kappou et al. (2008), Chen et al. (2019), and Chang et al. (2025), all of which rely on similar tests for average abnormal returns and cumulative average abnormal returns. In this present study, the null hypothesis states that average abnormal returns are equal to zero, whereas the alternative hypothesis assumes the existence of non-zero average abnormal returns. The same hypothesis is applied for cumulative average abnormal returns. Statistical significance is evaluated using a two-tailed t-test, which can be expressed as follows:

$$t = \frac{\bar{x}}{s/\sqrt{N}}$$

where $\bar{x}$ denotes the sample mean, s the sample standard deviation, and N the number of observations.

In the present context, the sample mean corresponds either to (1) the AAR_t or to (2) the $CAAR_{T_0,T_1}$. The corresponding test statistics are therefore given by:

(1) $$t = \frac{AAR_t}{s(AR_t)/\sqrt{N}}$$

(2) $$t = \frac{CAAR_{T_0,T_1}}{s\left(CAR_{T_0,T_1}\right)/\sqrt{N}}$$

The t-statistic measures the distance between the estimated mean and zero in units of its standard error. In a two-tailed test, statistical significance depends on the critical values chosen as thresholds for rejecting the null hypothesis. The most commonly used significance levels are 10%, 5% or 1%. For large samples, the corresponding critical values are approximately 1.645, 1.96, and 2.576, respectively. Accordingly, the null hypothesis is rejected at the 10% level if |t| ≥ 1.645, at the 5% level if |t| ≥ 1.96, and at the 1% level if |t| ≥ 2.576.

Finally, as a robustness check, the stationarity of the abnormal return series is assessed using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979). In this context, stationarity means that abnormal returns fluctuate around a stable mean rather than following a persistent trend. The null hypothesis of the ADF test is that the series is non-stationary, while the alternative hypothesis is that the series is stationary. Since the analysis is based on returns rather than price levels, stationarity is expected. Nevertheless, confirming stationarity is relevant because the t-tests on AAR and CAAR assume that abnormal returns are drawn from a stable return-generating process.

Although most of the empirical results are presented in the next section, the stationarity results are reported here as a diagnostic check. The ADF test is applied to 318 stock-event abnormal return series. The share of series classified as stationary at 5% is equal to 1, meaning that 100% of the tested abnormal return series reject the null hypothesis of non-stationarity. The mean ADF p-value is 1.40683×10^{-5}, which is below 0.05, which is well below 0.05, further supporting the conclusion that the abnormal return series are stationary.

5. Result

This section is structured as follows. First, the empirical results are presented. Second, these results are interpreted in light of the main hypotheses developed in the literature. Third, the cross-country analysis is introduced. Although it provides additional results, its interpretation remains limited due to sample size constraints. Finally, the section discusses the limitations encountered during the analysis and suggests possible ways to improve future research.

Table 1: Descriptive Statistics and Average Estimated Coefficients

Statistic	**Value**
Number of events	318
Mean number of observations	220.3994
Minimum number of observations	144
Maximum number of observations	221
Mean R^2	0.1945
Median R^2	0.1797
25th percentile R^2	0.1049
75th percentile R^2	0.2707
Mean σ_ϵ	0.0236
Median σ_ϵ	0.0204
Mean $\hat{\alpha}$	0.00017
Std. dev. $\hat{\alpha}$	0.00246
t-statistic $\hat{\alpha}$	1.246
Mean $\hat{\beta}_{mkt}$	1.08559***
Std. dev. $\hat{\beta}_{mkt}$	0.41003
t-statistic $\hat{\beta}_{mkt}$	47.213
Mean $\hat{\beta}_{smb}$	0.73362***
Std. dev. $\hat{\beta}_{smb}$	1.23755
t-statistic $\hat{\beta}_{smb}$	10.571
Mean $\hat{\beta}_{hml}$	-0.00845
Std. dev. $\hat{\beta}_{hml}$	0.69127
t-statistic $\hat{\beta}_{hml}$	-0.218
Mean $\hat{\beta}_{mom}$	-0.06934*
Std. dev. $\hat{\beta}_{mom}$	0.69425
t-statistic $\hat{\beta}_{mom}$	-1.781

This table reports descriptive statistics for the event-specific Carhart four-factor estimations. The reported t-statistics test whether the average estimated coefficient is significantly different from zero across events. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Our results follow the order of computation described in the methodology. The first step was to estimate the coefficients ($\widehat{\beta_{MKT,i}}$, $\widehat{\beta_{SMB,i}}$, $\widehat{\beta_{HML,i}}$, $\widehat{\beta_{MOM,i}}$, α_i) over the estimation window. The Python code is highly conservative: any unprocessable value, such as an infinite value, leads to the deletion of the corresponding stock. After estimating all coefficients, we obtain results for 318 observations. To improve the understanding of our analysis, a descriptive part is presented in Table 1.

Table 1 provides basic descriptive statistics over the estimation window. To begin with, the table reports key information regarding the mean, maximum and minimum number of observations. The mean number of observations, 220.3994, indicates that most of the added or deleted stocks cover almost the entire estimation window, which consists of 221 days. This result is also partially explained by the restriction established previously: if a stock had fewer than 30 observations either in the estimation window [AD-250, AD-30] or in the post-announcement window [AD-2, ED+60], it was not included in our analysis.

Following the statistics on the number of observations, the table provides a brief diagnostic of the heterogeneity of the regressions. The mean R^2 is equal to 19.45%. This means that, on average, the Carhart model used in this analysis explains approximately 19.45% of the variation in excess returns during the estimation window. The median R^2 is 17.97%, which is very close but slightly below the mean, suggesting that some stocks with relatively higher R^2 values pull the average upward. The 25th percentile of the R^2 distribution indicates that, for one quarter of the stocks in the sample, the model explains 10.5% or less of the return variation, while for 75% of the stocks, it explains 27.07% or less of the return variation. Finally, the mean σ_ε of 2.36% represents the average residual standard deviation, which can be interpreted as the percentage of return variation in the estimation window that is not explained by the factors. It can therefore be considered a measure of the idiosyncratic risk of the stock.

The second part of Table 1 demonstrates the explanatory power of the Carhart four-factor model, supported by a statistical t-test. The first information reported concerns the intercept α_i. The intercept represents the mean excess return that is unexplained by the explanatory variables and tests whether it is statistically different from zero. The average intercept is small, equal to 0.00017, and is not statistically significant. The market beta coefficient is statistically significant at 1% level, with a t-statistic of 47.213. The sample firms are therefore highly exposed to the market movements. The size factor is also positive and statistically significant, with a mean estimated coefficient of 0.73362. This indicates that the firms in our sample behave more like firms with small-cap characteristics than firms with large-cap characteristics, which is consistent with the MSCI World Small-Cap ex-U.S. Index. By contrast, the book-to-equity factor is not significant, indicating no clear value effect. Finally, Table 1 shows that the estimated momentum coefficient is negative and statistically significant, but only at 10%.

The analysis of Table 2 is divided into two panels: Panel A focuses on the announcement date [AD-2, AD+2], while Panel B focuses on the effective date [ED-2, ED+2], following the approach of Chen et al. (2019). The underlying idea is that most of the return variation occurs around these events. The announcement date is when most of the information effect, and by extension the arbitrage activity, takes place. The effective date is when index-tracking institutions are forced to buy stocks added to the index or sell stocks deleted from the index. These two panels are constructed using data from the four quarterly months, and the windows are defined relative to AD and ED, which differ for each month. For the four months reviewed in 2025, we obtained 155 additions and 163 deletions.

Table 2: Average Abnormal Returns around Announcement and Effective Days

Event day	Additions		Deletions	
	Mean (%)	t-stat.	Mean (%)	t-stat.
Panel A: Announcement day (AD)				
-2	0.034	0.12	−0.132	−0.56
-1	0.170	0.76	0.245	0.96
AD	−0.259	−1.24	0.001	0.00
+1	−0.102	−0.37	−0.573**	−2.12
+2	−0.393**	−2.09	0.218	0.92
Panel B: Effective day (ED)				
-2	−0.043	−0.22	0.264	1.22
-1	−0.613**	−2.55	0.460**	2.02
ED	−0.902***	−3.77	−0.787***	−2.65
+1	−0.381	−1.52	0.905***	3.43
+2	−0.178	−0.69	0.337	0.74

Note. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed t-tests.

Regarding additions, in Panel A, apart from [AD+2], which presents a negative average abnormal return of -0.393%, none of the other days are statistically significant. Around the effective date, ED-1 and ED are statistically significant and show negative average abnormal returns. Observing negative average abnormal returns for addition is quite surprising, as it goes against previous expectations. The temporary or permanent nature of these abnormal returns cannot be determined from this specific table, since ED+1 and ED+2 are both insignificant.

Concerning deletions, we note that on the announcement day and during the two days before the announcement, none of the results is statistically significant. During the day after the announcement, statistically significant negative average abnormal returns are reported at the 5% level. AD+2, like AD-2, AD-1 and AD, present insignificant results, making them difficult to interpret. For the effective dates, the results obtained between [ED-1, ED+1], show respectively average abnormal returns of 0.46%, -0.79%, and 0.91%. All of them are statistically significant.

Table 3: Cumulative Abnormal Return Interval

Event window	**Cumulative Abnormal Returns**			
	Additions		**Deletions**	
	Mean (%)	**t-stat.**	**Mean (%)**	**t-stat.**
AD to ED−1	−2.800 ***	−3.35	1.021	1.27
AD to ED+20	−6.397 ***	−4.46	3.576 ***	2.96
AD to ED+40	−6.862 ***	−3.54	4.939 ***	2.93
AD to ED+60	−9.260 ***	−3.96	6.104 ***	2.76

Note. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed t-tests.

The following table 3, reports the Cumulative Average Abnormal Returns (CAARs) for the different sub-event windows [AD, ED+20], [AD, ED+20], and [AD, ED+60], as well as the event window [AD, ED-1]. The first characteristic that emerges from the table is the high level of statistical significance. Except for the CAAR of the event study for deletions, all other results are significant at the 1% level.

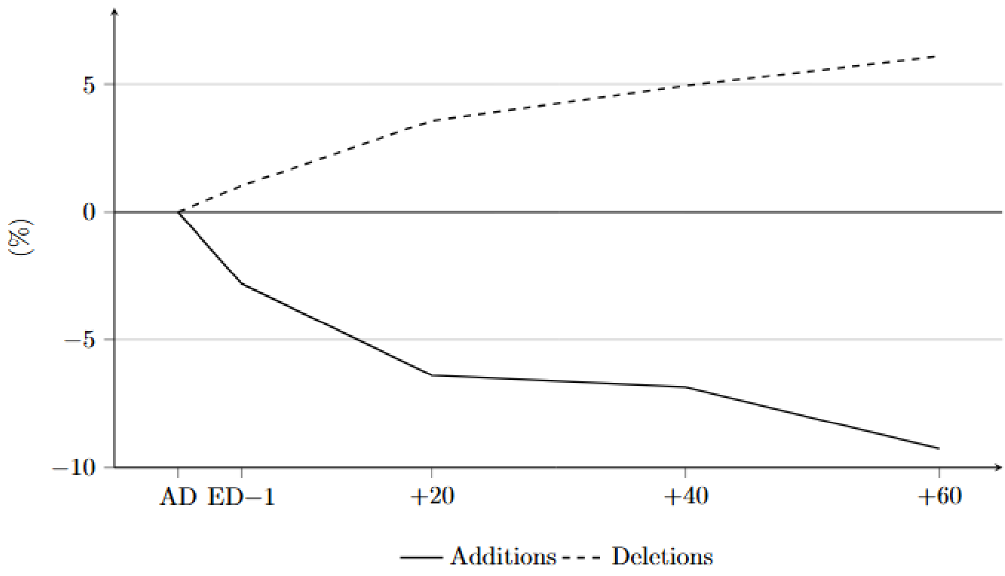

Figure 5: Cumulative Average Abnormal Returns (CAAR) from AD to ED+60

We identify overall negative abnormal returns for stocks added to the index, ranging from -2.800% in the event window to -9.260%, representing a total increase in negative abnormal returns of -6.460%. By contrast, deletions are associated with positive abnormal returns, ranging from 3.576%[6] to 6.104%, representing an increase of 2.528%. These trends are opposite to almost all of the existing literature. For instance, Chakrabarti et al. (2005) find a CAAR of 3.96% for additions and -5.01% for deletions over the event window [AD, ED+10]. Another important example is Chen et al. (2019), which is even more relevant because it uses the same windows. For the 2009-2015 period in developed countries, they observe a CAAR of 2.947% for additions and -4.484% for deletions over the window [AD, ED-1]. These trends remain positive for additions and negative for deletions over the windows [AD to ED+20] and [AD to ED+40]. In Chen et al. (2019), we also observe a reversal effect in abnormal returns over the window [AD to ED+60], which is not the case in our sample. In our results, additions generate increasingly negative abnormal returns, while deletions generate increasingly positive abnormal returns. Figure 5 illustrates this permanent effect.

5.1 Interpretation of Results and Hypotheses

This section aims to verify, with the support of our empirical results, which hypothesis our findings are most consistent with. The main hypotheses considered are the Price Pressure Hypothesis, the Downward-Sloping Demand Curve Hypothesis, and the Investor Recognition Hypothesis.

Unfortunately, the Liquidity Cost Hypothesis and the Information Content Hypothesis cannot be fully assessed in this study, because the analysis relies exclusively on daily total returns. Testing the Liquidity Cost hypothesis would require liquidity measures, such as bid-ask spreads, trading volume or transaction costs proxies, which are not included in the present dataset. Similarly, testing the Information Content hypothesis would require evidence that the index change conveys new information to the market. Although average abnormal returns around the announcement date may indicate a market reaction, they do not allow us to determine whether this reaction is driven by new information rather than by mechanical index trading. For instance, Jain (1987) examines firms added to supplementary S&P indexes that were not expected to be tracked by index funds in order to distinguish between information effects and price pressure. A similar

[6] Starting with the statistically significant window [AD, ED+20]

identification strategy would be required to test the Information Content Hypothesis more directly in this study.

Before beginning the hypothesis analysis, it is necessary to acknowledge the disappearance effect. Kappou (2018), in his study of S&P 500 additions, supports the disappearance effect by mentioning that the “S&P Game”, whereby traders buy at the announcement date and sell close to the effective date at a profit, no longer holds. As a result, he finds a very small and statistically insignificant abnormal return (-0.10%) around the effective date after the 2008 financial crisis, while the demand shock on the day after the announcement remains present, with a significant positive price pressure of 3.01%. In our case, the abnormal return at AD+1 is significant for deletions but insignificant for additions, while abnormal returns are still observed at ED. Since the disappearance effect is associated with weaker significance around the effective date and across the event window, our results do not fully support this pattern. Indeed, our study reports strongly significant results for additions over the window from [AD to ED-1], which contradicts this disappearance effect. Nevertheless, Kappou (2018) relies on a time comparison between a pre- 2008 crisis sample and a post-crisis sample, which we do not have. Therefore, the disappearance assumption cannot be fully rejected. With improvements in data accessibility, a more complete conclusion could be reached, as discussed in the next section (n°6).

Before interpreting Tables 2 and 3, it is important to recall that the results are expressed in terms of negative abnormal returns, not raw stock returns. A negative abnormal return does not necessarily imply that the stock generated a negative raw return or that its price decreased. It means that the realized return was lower than the return predicted by the Carhart four-factor model. Since the normal return is estimated using market, size, value, and momentum factors, the benchmark is more demanding than a simple market-model benchmark. This is especially relevant in our sample, which is composed of small-cap stocks. The average estimated market and size loadings are positive, with $\beta_{MKT} = 1.0856$ and $\beta_{SMB} = 0.7336$, respectively. Therefore, when the market and small-cap factors perform positively during the event window, the Carhart model predicts relatively normal returns. If the realized return is positive but lower than this predicted normal return, the abnormal return becomes negative. Thus, the negative abnormal returns should be interpreted as relative underperformance compared with the Carhart-implied benchmark, rather than as evidence of absolute price declines.

Tables 2 and 3 together help determine which hypothesis our findings are most consistent with. In Panel A of Table 2, deletions exhibit statistically significant abnormal returns around the announcement date, whereas no comparable significant reaction is observed for additions. Around the effective date, both additions and deletions exhibit negative average abnormal returns. However, deletions display positive abnormal returns at ED+1, suggesting a short-term reversal relative to the Carhart benchmark. This pattern is broadly consistent with a short-term price-pressure mechanism for deletions, although the evidence remains based on abnormal returns rather than raw price movements. Therefore, the results should be interpreted as relative underperformance or overperformance compared with the predicted normal return, not as direct evidence of absolute price decreases or increases.

Continuing our analysis with Table 3 provides evidence on whether the abnormal return pattern appears persistent or temporary, which helps compare the empirical results with the main theoretical hypotheses. We observe a persistent cumulative abnormal return pattern for both additions and deletions. Abnormal returns gradually increase across the different windows: [AD to ED-1], [AD to ED+20] and [AD to ED+40] and [AD to ED+60], suggesting that the abnormal return pattern does not quickly reverse after the effective date. This persistent pattern is difficult to reconcile with a pure Price Pressure Hypothesis, which predicts temporary price effects followed by reversal. The results are also not fully consistent with the Investor Recognition Hypothesis, since this hypothesis predicts a more temporary effect for deletions.

The persistence of the abnormal returns is closer to the prediction of the Imperfect Substitutes Hypothesis, or Downward-Sloping Demand Curve Hypothesis, since the permanent aspect of the effect is aligned with this hypothesis. However, the sign of the abnormal returns is not fully aligned with the standard prediction of this hypothesis. Under the Downward-Sloping Demand Curve

Hypothesis, additions are expected to experience positive price pressure due to index fund buying, while deletions are expected to experience negative price pressure due to index-fund selling. In our results, additions underperform relative to their Carhart-predicted normal returns, while deletions show positive cumulative abnormal returns over longer windows. Therefore, although the persistence of the effect is consistent with the hypothesis the direction of the abnormal returns is not. This suggests that Downward-Sloping Demand Curve hypothesis alone cannot fully explain the results.

These abnormal-return patterns are relatively rare in the literature. After conducting additional research on cases where additions are associated with negative abnormal returns and deletions with positive abnormal returns, one article stands out: Bennett et al. (2020).

Bennett et al. (2020), through their empirical study of S&P 500 constituent changes over the 1997-2017 period, document long-term negative abnormal returns for added stocks relative to a Carhart four factor benchmark. More precisely, using the Carhart four-factor model, they report a CAAR of -0.021 (-2.1%) over the window [AD-5, AD+21]. Their explanation for this phenomenon is multifaceted.

First, once a firm joins the index, it becomes increasingly owned by passive investors and blockholders. Because of this passive ownership, investors have less incentive to collect firm-specific information or monitor the management situation. As managerial oversight decreases, the firm's governance environment becomes less effective, potentially harming the long-term performance.

Second, again because of passive ownership, the stock price may convey less information about the firm. The stock price may become more aligned with the other members of the index. Since more informative stock price help managers make better decisions, a decline in price informativeness means that managers learn less from the market and investors become less efficient.

Third, companies added to the S&P 500 suffer from a categorical effect. More specifically, firms joining the index become part of a reference group, resulting in greater comparison with other index members by the board and the managerial team. This comparison leads managers and board members to align policies and procedures with those of other index constituents, even if these changes do not improve firm fundamentals. Benett et al. (2020) show that even though credit ratings improve, the firm's ROA decreases.

Overall, Benett et al. (2020) could be related to the disappearing-effect literature because they note that the old announcement effect of the S&P 500 has largely disappeared. However, the long-term negative abnormal returns documented in the later period, 2008-2017, are not strictly part of the disappearing effect. Our results may be consistent with this type of long-term underperformance, although this interpretation remains tentative. It remains difficult to provide a clear conclusion for two reasons. First, Benett et al. (2020) focus only on additions and on a different index, which makes direct comparison difficult. Second, our paper does not provide data over previous years, making the disappearance effect difficult to detect.

5.2 Cross-Country analysis

Apart from Chakrabarti et al. (2005) and Chen et al. (2019), relatively few studies analyze the index effect across countries. The use of MSCI indices in event studies makes this type of cross-country analysis possible, since MSCI include firms from several national markets. While this paper primarily examines whether abnormal returns are present around rebalancing events of the MSCI World Small-Cap ex-U.S. Index, it also conducts a country-level CAAR analysis by dividing the sample according to the countries included in the index.

Tables 4 and 5 report the CAARs for the event window [AD, ED-1] and the longer sub-event window [AD, ED+60], respectively, for each country included in the MSCI World Small-Cap ex-U.S. Index, except Canada, which is excluded. Both tables show very few statistically significant results, mainly because several countries have a small number of observations.

In Table 4, Australia displays the largest statistically significant CAARs, with a negative CAAR of -7.1% for additions, significant at the 1% level, and a positive

CAAR of 5.7% for deletions, significant at the 10% level, over the event window. Japan records a negative CAAR of -1.7% for additions and a positive CAAR of 3.0% for deletions; however, only the deletion result is statistically significant at the 5% level. Another major contributor to abnormal returns is the United Kingdom, where both additions and deletions display statistically significant negative CAARs of -4.4% and -3.7%, respectively.

In Table 5, Australia follows the same pattern as in the event window, with CAARs of -12.1% for additions and 20.7% for deletions. The CAARs for Japanese deletions are no longer statistically significant. The CAARs for the United Kingdom additions also become insignificant, while deletions show a significant reversal effect, with a positive CAAR over the longer window. Finally, Sweden should be mentioned, as its deletion CAAR moves from -4.3%, with a low level of significance in Table 4, to almost twice that value in Table 5, with a CAAR of 8%.

Table 6 attempts to address the limited-significance issue by grouping European countries together, except for the United Kingdom. The United Kingdom is treated separately because it has more additions and deletions than most other European countries and would therefore have a disproportionate influence on the European group. Japan and Australia constitute the other main country groups. Other values from Oceania or Asia are not taken into account, as they are judged negligible for this analysis. Table 6 also reports the CAAR analysis for all the post-announcement windows considered in this paper. The results show that Europe as a whole generates significant negative CAARs for additions, especially for the [AD, ED-1] window, with a CAAR of -13.227%.

Table 4: CAAR results for event window AD to ED−1

Country	Type	Obs.	CAAR (%)	CAAR std. (%)	t-stat.
AUSTRALIA	Addition	31	-7.1***	10.3	-3.854
AUSTRALIA	Deletion	19	5.7*	13.6	1.827
AUSTRIA	Addition	2	-12.1	20.4	-0.839
AUSTRIA	Deletion	2	8.0	12.6	0.900
BELGIUM	Addition	2	0.3	1.6	0.277
BELGIUM	Deletion	1	8.1	NAN	NAN
DENMARK	Addition	2	-1.3	8.7	-0.214
DENMARK	Deletion	2	-0.6	20.5	-0.044
FINLAND	Deletion	1	3.0	NAN	NAN
FRANCE	Addition	12	-1.6	12.9	-0.429
FRANCE	Deletion	3	6.9	11.0	1.086
GERMANY	Addition	5	0.7	6.7	0.238
GERMANY	Deletion	11	-4.3	9.4	-1.502
HONG KONG	Addition	2	2.4	2.9	1.175
ISRAEL	Addition	14	-2.0	9.7	-0.757
ISRAEL	Deletion	4	5.3	7.5	1.415
ITALY	Addition	5	-5.6	11.6	-1.089
ITALY	Deletion	3	-1.5	5.6	-0.453
JAPAN	Addition	28	1.7	12.7	0.724
JAPAN	Deletion	59	3.0**	10.8	2.107
NETHERLANDS	Deletion	1	5.3	NAN	NAN
NEW ZEALAND	Addition	1	-4.7	NAN	NAN
NEW ZEALAND	Deletion	1	-0.4	NAN	NAN
NORWAY	Addition	4	4.2	12.2	0.698
NORWAY	Deletion	3	-0.6	6.8	-0.151
PORTUGAL	Deletion	1	-3.0	NAN	NAN
SINGAPORE	Addition	6	-4.8	9.0	-1.304
SINGAPORE	Deletion	1	1.2	NAN	NAN
SPAIN	Addition	1	-8.0	NAN	NAN
SPAIN	Deletion	6	-3.0	5.9	-1.235
SWEDEN	Addition	13	-4.3*	7.2	-2.165
SWEDEN	Deletion	7	-3.9	6.2	-1.679
SWITZERLAND	Addition	9	-1.1	9.7	-0.354
SWITZERLAND	Deletion	9	1.9	9.7	0.587
UNITED KINGDOM	Addition	18	-4.4**	6.6	-2.822
UNITED KINGDOM	Deletion	29	-3.7***	7.0	-2.823

Notes: *** 1%, ** 5%, * 10%; NAN = not available.

Table 5: CAAR results for event window AD to ED+60

Country	Type	Obs.	CAAR (%)	CAAR std. (%)	t-stat.
AUSTRALIA	Addition	31	-12.1**	27.5	-2.440
AUSTRALIA	Deletion	19	20.7**	41.3	2.183
AUSTRIA	Addition	2	-8.9	52.3	-0.240
AUSTRIA	Deletion	2	17.8	44.1	0.571
BELGIUM	Addition	2	1.5	21.6	0.099
BELGIUM	Deletion	1	21.6	NAN	NAN
DENMARK	Addition	2	-40.3	76.0	-0.750
DENMARK	Deletion	2	6.9	24.9	0.391
FINLAND	Deletion	1	22.3	NAN	NAN
FRANCE	Addition	12	-2.9	31.4	-0.319
FRANCE	Deletion	3	14.8	23.4	1.096
GERMANY	Addition	5	8.5	26.0	0.728
GERMANY	Deletion	11	6.0	26.9	0.742
HONG KONG	Addition	2	-42.6	56.4	-1.069
ISRAEL	Addition	14	-0.1	31.3	-0.012
ISRAEL	Deletion	4	-9.8	25.3	-0.777
ITALY	Addition	5	-22.5*	20.5	-2.453
ITALY	Deletion	3	9.1	51.7	0.305
JAPAN	Addition	28	-0.4	26.1	-0.076
JAPAN	Deletion	59	1.3	22.3	0.440
NETHERLANDS	Deletion	1	-8.5	NAN	NAN
NEW ZEALAND	Addition	1	7.0	NAN	NAN
NEW ZEALAND	Deletion	1	0.2	NAN	NAN
NORWAY	Addition	4	-11.3	16.2	-1.400
NORWAY	Deletion	3	-17.4	51.0	-0.592
PORTUGAL	Deletion	1	-16.4	NAN	NAN
SINGAPORE	Addition	6	-22.0*	24.0	-2.246
SINGAPORE	Deletion	1	14.4	NAN	NAN
SPAIN	Addition	1	-37.7	NAN	NAN
SPAIN	Deletion	6	4.3	6.4	1.659
SWEDEN	Addition	13	-32.8***	27.6	-4.288
SWEDEN	Deletion	7	-2.1	41.6	-0.133
SWITZERLAND	Addition	9	-2.0	35.1	-0.170
SWITZERLAND	Deletion	9	17.2	39.2	1.320
UNITED KINGDOM	Addition	18	-6.2	18.1	-1.457
UNITED KINGDOM	Deletion	29	8.0**	20.6	2.084

Notes: *** 1%, ** 5%, * 10%; NAN = not available.

Table 6: CAAR results by event window for Australia, Europe, Japan, and UK

	Australia		Europe		Japan		UK	
Event window	**Addition**	**Deletion**	**Addition**	**Deletion**	**Addition**	**Deletion**	**Addition**	**Deletion**
AD to ED−1	-7.108*** (-3.854)	5.700* (1.827)	-2.325* (-1.715)	-0.648 (-0.522)	1.742 (0.724)	2.968** (2.107)	-4.370** (-2.822)	-3.680*** (-2.823)
AD to ED+20	-9.791*** (-2.820)	6.220 (1.486)	-5.523** (-2.111)	3.684 (1.631)	-2.579 (-0.839)	2.994 (1.592)	-7.578** (-2.554)	3.824 (1.403)
AD to ED+40	-10.441** (-2.457)	15.403* (2.002)	-6.485* (-1.771)	4.734 (1.435)	-2.206 (-0.493)	2.319 (1.091)	-7.526 (-1.727)	5.469* (1.700)
AD to ED+60	-12.057** (-2.440)	20.678** (2.183)	-13.227*** (-3.027)	6.412 (1.429)	-0.377 (-0.076)	1.277 (0.440)	-6.221 (-1.457)	7.960** (2.084)

Notes: Entries report CAAR in percent, with t-statistics in parentheses. *** 1%, ** 5%, * 10%.

5.3 Limitations and future improvements

This section discusses the limitations encountered during this study and provides insights into how future similar research could be enhanced in order to avoid these issues.

The main limitation of the study is related to data availability. The software used, LSEG Datastream, as well as Bloomberg, often requires additional subscriptions to provide direct and clear access to constituent changes in MSCI indices. The academic version of these platforms may not be sufficient for this purpose. This data limitation reduced the size of the sample selected for this study. With broader access to historical constituent-change data, a study over a longer period, as frequently conducted in the literature (Chakrabarti et al., 2005; Chen et al., 2019; Chen et al., 2004), would be more relevant, especially for carrying out cross-period analysis.

Access to a longer period could, for instance, provide more evidence regarding the disappearance effect. As previously mentioned, this effect could only be partially assessed in our study due to the absence of previous data that could be compared with our sample, such as the pre-crisis event window used by Kappou (2018). In addition, another important paper on the disappearing Index effect is Greenwood & Sammon (2023) who identify the effect by comparing the CAARs around the announcement date [AD-1, AD+1] and the effective date [ED-1, ED+1] across several decades for the S&P 500. According to them, additions generated CAARs of 3.4% in the 1980s, 7.4% in the 1990s, 5.2% in the 2000s, and around 1% in 2010s. For deletions, the corresponding figures are -4.6%, -16.1%, -12.4%, and around -0.6% in the 2010s. One could therefore imagine applying their methodology to the MSCI World Small-Cap ex-U.S. Index over several years prior to 2025 in order to clearly identify whether a disappearance effect is present.

Another limitation concerns the composition of the sample. Although the sample is diversified at the country level, it does not compare between countries with different types of financial markets, such as developed and emerging markets. This comparison could be particularly interesting because, while developed markets often show limited abnormal returns, Chen et al. (2019) show that emerging markets are more sensitive to rebalancing events and are more likely to generate abnormal returns.

A cross-capitalization comparison would also be interesting. For instance, Ernest and Yuabin (2024) propose a study of abnormal return variation between stocks moving across the S&P 500, S&P 400 and S&P 600 Small-Cap indices. While our study can be compared with recent studies such as Chang et al. (2025) or Chen et al. (2019), the period from which the sample is drawn and the sample size differ. The advantage of conducting a recent and relatively specific study of the MSCI World Small-Cap ex-U.S. Index is therefore offset by the reduced possibilities of direct comparison with the existing literature.

Another limitation is that this study does not, by itself and based on empirical evidence, explain the cause or origin of these abnormal returns observed. Identifying these mechanisms often requires more complex computations and, once again, may not be feasible due to data limitations.

Last but not least, trading volume is often analyzed alongside stock returns, as it can provide additional insights into the intensity of market reactions and the mechanisms behind abnormal returns. However, still due to data limitations, this dimension of the literature could not be incorporated into the present study. Including trading volume would have allowed us to distinguish more clearly between temporary price pressure, liquidity-driven effects and information-based reactions around index rebalancing events. Future research could therefore extend the analysis by examining abnormal trading volume before and after index changes, in order to better understand whether the observed return patterns are associated with changes in investor trading behavior.

6. Conclusion

With the increase in institutional investors tracking indices and the important role these indices play in portfolio management, it is essential to gather as much information as possible about events that may have a significant impact on them. Changes in index constituents have been a central topic in the financial literature. These rebalancing events, especially in the context of the S&P 500, have been shown to generate abnormal returns on the announcement date of the changes, as well as during their implementation. This phenomenon is commonly referred to as the index effect.

The underlying intuition is that institutional investors must track these indices very closely, generating forced buying or selling around the implementation date of changes in the tracked index. In addition, abnormal returns may arise after the announcement date due to new information released to the market. The purpose of this paper is to broaden this general intuition by detecting the presence of abnormal returns around the four quarterly reconstitution events of the MSCI World Small-Cap ex-U.S. Index in 2025. Therefore, this paper answers the following research question:

"Did the 2025 MSCI World Small Cap ex-US Index reconstitution lead to abnormal stock returns around the announcement and implementation dates?"

Our analysis also provides key insights into the potential hypotheses explaining the presence of these abnormal returns. The literature on index constituent changes has developed five main hypotheses: the Price Pressure Hypothesis, the Downward-Sloping Demand Curve Hypothesis, also referred to as the Imperfect Substitute Hypothesis, the Investor Recognition Hypothesis, the Information Content Hypothesis, and the Liquidity Cost Hypothesis. The disappearing index effect is also taken into account, given the recent nature of this paper and because it could partially explain the results in the case of weak significance or relatively low abnormal returns. In summary, these hypotheses differ in their theoretical explanations and, most importantly, in their predictions regarding the persistence of the abnormal returns after implementation, especially whether the effect is temporary or permanent.

To conduct this analysis, we retrieved daily total returns for the index constituents from LSEG Datastream and used the Carhart four-factor model, which is an improved version of the Capital Asset Pricing Model (CAPM), to identify the presence of abnormal returns. This model allows us to control not only for market exposure, but also for size, momentum, and book-to-equity exposure, which could explain part of the abnormal returns.

The study follows the event-study framework of MacKinlay (1997) and implements different windows relative to the announcement date (AD) and the effective date (ED) of constituent changes. A pre-estimation window [AD-250, AD-30], and event window [AD, ED-1], and several longer event windows, designed to capture the persistence of the effect over time [AD, ED+20],[AD, ED+40], and [AD, ED+60], are defined. We then computed the normal returns for the windows after the announcement date by estimating the factor coefficients over the estimation window. These same coefficients, free from event contamination, are then used in the event study to calculate the normal return. Abnormal returns are obtained by subtracting normal returns from actual returns for the different selected window. This methodology provides abnormal returns at the stock level and is repeated for all stocks, either added or deleted from the MSCI World Small-Cap ex-U.S. Index. After abnormal returns are obtained, cumulative average abnormal returns and average abnormal returns are computed for each day using standard calculations. The cumulative average abnormal return is then obtained by averaging the cumulative abnormal returns.

The main empirical findings show the presence of negative average abnormal returns for stocks added to the index and positive average abnormal returns for deleted stocks. These abnormal returns should be interpreted relative to the Carhart-predicted normal return, rather than as direct evidence of absolute price decreases or increases. Our analysis focuses on average abnormal returns around AD and ED. The day after the announcement shows no significant result for additions, while deleted stocks followed a more traditional path with negative average abnormal returns that reverted the following day. The effective date shows negative average abnormal returns for stocks added to the index and for deleted stocks, but only at ED. Deletions show a strong reversal effect, with positive average abnormal returns on ED+1 and ED+2. This trend around the implementation date continues on a broader scale, with negative cumulative average abnormal returns over the long-term windows for additions and positive cumulative average abnormal returns for deletions. The cumulative average abnormal return analysis suggests that the abnormal return patterns persist over the event windows considered. This evidence is not fully consistent with the Price Pressure Hypothesis or the Investor Recognition Hypothesis, both of which imply more temporary effects followed by reversal.

We interpret our results as providing evidence of abnormal returns, although no significant abnormal returns are found at AD+1 for stocks added to the index, while some significant effects are observed at AD+2. Concerning the possible explanation of these results using existing hypotheses, the findings are not fully aligned with the traditional predictions of the main index effect hypotheses. The disappearing effect could be a potential interpretation, but it would require a broader time span to be properly tested. The Information Content Hypothesis and the Liquidity Cost Hypothesis cannot be fully assessed, as they require additional evidence and data.

The paper also proposes a cross-country analysis, which helps identify the regions most affected by abnormal returns, namely Europe, Australia and the United Kingdom. These results are heterogeneous and indicate that national market characteristics may influence the index effect. This short section of the paper opens the door to further research focusing on cross-country differences.

To conclude, our empirical study of constituent changes in the 2025 MSCI World Small-Cap ex-U.S. Index demonstrates the presence of abnormal returns around rebalancing events. However, the direction of these abnormal returns is not fully consistent with the traditional hypotheses, suggesting that the conventional Price Pressure Hypothesis, Downward-Sloping Demand Curve Hypothesis, and Investor Recognition Hypothesis may not fully capture the dynamics of small-cap index rebalancing. The disappearing effect remains a possible interpretation of our findings. These unusual results invite further research into small-cap indices in recent years. Further studies could extend this analysis across several rebalancing periods, compare small-cap and large-cap indices, and examine the causes of national differences.

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Artificial intelligence tools, in particular ChatGPT, were used solely to improve sentence formulation and correct grammar throughout the thesis. These tools were used only for language editing purposes and did not alter the content, analysis, interpretation, or conclusions of the work.

List of Appendices

Appendix A – Code python of ISIN matching process

```
#%%

#################
## ISIN Lookup ##
#################

# Import modules
import pandas as pd
import os
import re

# Set directories
code = r"C:\Users\theol\Documents\Prague\Master thesis\data\Code"

# Read excel sheets
adddel = pd.read_excel(os.path.join(code,"AddDel_2024.xlsx"))
ISIN = pd.read_excel(os.path.join(code,"AGI Benchmark Equity Monthly 202510
vtheo.xlsx"), sheet_name = "Sheet10")

# Add ISIN column
adddel["ISIN"] = None

# Loop through companies
```

```
nonfound = []
multiple_matches = []

companies = adddel["Company"]

for comp in companies:
    exclbrack = re.sub(r"\s*[\(\[\{].*?[\)\]\}]\s*", " ", comp).strip()
    exclBs = re.sub(r"\bB\b", "", exclbrack)

    first_two = " ".join(exclBs.split()[:2])
    mask = ISIN["INSTRUMENT NAME"].str.contains(first_two, case=False, na=False)
    matches = ISIN[mask]

    if matches.empty:
        nonfound.append(comp)
        print(f"{comp} not found")
        continue

    unique_isins = matches["ISIN"].unique()

    if len(unique_isins) == 1:
        # Exactly one unique ISIN
        isin_code = unique_isins[0]
        adddel.loc[adddel["Company"] == comp, "ISIN"] = isin_code
    else:
        # Multiple different ISINs
```

```
        multiple_matches.append(comp)
        print(f"{comp} has multiple ISINs: {list(unique_isins)}")

# Checking non found and multiple found
len(nonfound)
len(multiple_matches)

# Upload File
adddel.to_excel(os.path.join(code,"adddel_code_2024.xlsx"), index=False)


# %%
```