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The Influence of Firm Size and ETFs on the Index Inclusion Effect

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1. Introduction

Since the invention of the Exchange Traded Fund also known as an ETF, in 1993, passive investing has become a behemoth in the investing world. According to Seyffart (2021), passive investing overtook the U.S. equity market in 2018, which used to be dominated by active investors. In 2021, passive investors owned 53.8% of the U.S. market. This drastic change in the investing landscape has huge implications for the pricing of equities. If more than half of investors skip the process of price discovery and instead buy a stock passively because it is part of an index, traditional hypotheses of efficient markets have to be reconsidered. Can the price of a stock still represent the value of a company based on all publicly available information if half of the investors don’t even analyze the information? This also begs the question of what happens to a stock’s price when it gets included in one of these followed indices. As it turns out, the price seems to spike for additions and decline for deletions on the announcement day. This was named the Index Inclusion Effect (IIE). The reasons for this effect have been studied since the 1980s. With this thesis, I want to answer the question of the difference in the IIE between different firm sizes since the increasing popularity of ETFs. This research could shed new light on the current strength of the effect and the reasons for it. Could it be that ETFs have made the effect more extreme due to higher demand shocks, or have they reduced it due to the market efficiency provided by them? This would have a substantial significance for investors trying to achieve abnormal returns using the index inclusion effect.

2. Theoretical Background

The following part of the thesis reviews the most common theories that are used to explain the IIE and presents the results for each of them. I will also summarize findings looking at the influence firm size and passive investing have on observed abnormal returns after an index event.

2.1 Price Pressure Hypothesis

Harris and Gruel (1986) were some of the first to bring forth a theory explaining why newly added (deleted) securities show a positive (negative) abnormal return after inclusion (exclusion). They argued that the effect is caused by a shift in demand from index funds. Those who accommodate this new demand need to be compensated for transaction costs and portfolio risks. These liquidity providers are attracted by price increases caused by large purchases and compensated by a subsequent price drop. Therefore, selling the security above its fundamental value and repurchasing it at its fundamental value afterwards. The opposite goes for exclusions. Harris and Gruel argue that this effect is only temporary, and that the stock price returns to its fair value. This is in line with the efficient market hypothesis (EMH) in the long term because in both cases the demand for the security is perfectly elastic, but it differs in the short-term because the price pressure hypothesis (PPH) advocates for a less than perfectly elastic demand curve.

Blouin et al. (2000) found evidence supporting the PPH. They looked at the S&P 500 and found the prices of firms changed temporarily in order to compensate shareholders for any capital taxes that came into effect when selling securities to index funds. Lynch and Mendenhall (1997) find supporting evidence for the hypothesis in the S&P 500, but found it was stronger for deletions. Jain (1987) found that the IIE seems to be of a permanent nature when looking at the S&P 500, which speaks against the PPH. Jain (1987) looked at inclusions from the S&P 500 during 1977 and 1983. He found an abnormal return of 3.07% on the announcement date for inclusions, which reverses to essentially zero in the days after. Jain also compared the abnormal return with stocks added to a supplementary index which, was not widely followed by index funds. He finds that there is no significant difference between the two and therefore concludes that the PPH does not explain the IIE.

2.2 Downward Sloping Demand Curve Hypothesis

Proposed by Scholes (1972) and Shleifer (1986), the downward sloping demand curve hypothesis goes against the efficient market hypothesis. It states that the return response after the addition demonstrates an outward shift of the demand curve. Prices of newly added securities need to increase in order to eliminate the new excess demand. Harris and Gruel (1986) called this the “Imperfect Substitutes Hypothesis or Distribution Effect Hypothesis”. Shleifer looked at the cumulative average abnormal returns (CAARs) for stocks added to the S&P 500 between 1976 and 1983. He found a CAAR of 2.79% on the announcement day, and it stayed positive for at least 60 days after. This shows evidence for the price shift being permanent, supporting the hypothesis of a downward sloping demand curve. Mase (2007) found similar evidence supporting the DSDCH for the S&P 500. Petajisto (2011) also showed that the steepness of the demand curve seems to be negatively correlated with firm size. All the findings mentioned in Section 2.1 that support the price pressure hypothesis can be considered as evidence that speaks against the downward sloping demand curve hypothesis. If the DSDCH is to be believed, several established financial theories that rely on the efficient market hypothesis, such as the capital asset pricing model, need to be reevaluated amid new evidence disproving the validity of assuming perfectly elastic demand curves for securities.

2.3 Liquidity Hypothesis

Initially proposed by Woolridge and Ghosh (1986) and Amihud and Mendelson (1986), the liquidity hypothesis states that when a stock is newly added to an index, the liquidity increases and therefore reduces the bid-ask spread. Investors who want to buy or sell a stock when a large bid-ask spread is present, face a trade-off between waiting to buy or sell at a better price or trading now and facing a premium when buying and a discount when selling the stock, according to Amihud and Mendelson (1986). The new liquidity created by the index inclusion reduces the bid-ask spread and therefore the risk of the security. This in turn reduces the expected return from investors. A reduced expected return implies a rise in the price of a security. The liquidity hypothesis therefore also assumes the effect to be permanent, which is similar to the downward sloping demand curve hypothesis. When a stock gets excluded from an index, the opposite happens, as liquidity decreases and the increased risk causes a higher expected return for investors. Becker-Blease and Paul (2010) have looked at different causes for the index inclusion effect for the S&P MidCap 400 and the S&P SmallCap 600 indices. They have concluded that the main explanation for abnormal returns after inclusion is the increase in liquidity observed afterwards. They also found that the increased attention a stock generates after inclusion also partly explains this increase. Maldhavan (2015) has looked at the importance of liquidity for changes in index composition in the Russell 2000 index and found similar evidence supporting the liquidity hypothesis. Hegde and McDermott (2004) have found evidence showing liquidity improves after addition to the S&P 500 and deteriorates after deletion. There seems to be a consensus in the literature on the importance the change in liquidity after index revisions has for the index inclusion effect.

2.4 Attention Hypothesis

The attention hypothesis was first formulated by Odean (1999). He argues that investors face the problem of having to choose between thousands of stocks in which to invest. The time needed to analyze all of them, exceeds the time that can be spent. Investors therefore only invest in stocks they are aware of. The decision to buy is based on personal preferences. This can happen through mentions in news articles or when a stock shows an abnormal daily trading volume or return. The attention hypothesis only applies to the purchase of stocks, because an investor can only sell a stock if it is already known. Another reason why this hypothesis applies more to purchases is the fact that investors short securities more rarely compared to buying them. This differentiates the attention hypothesis from all other hypotheses that will be mentioned in this thesis. Merton (1987) has shown that stocks that are more visible seem to garner greater attention from investors. He used media coverage as a proxy for attention. This is known as the Merton attention model. An increase in media coverage or the number of shareholders after an addition are indicators used to support the attention hypothesis. Evidence supporting the attention hypothesis for the index inclusion effect is presented by Chen et al. (2004) and Elliott et al. (2006) when looking at the S&P 500. As mentioned in Section 2.3, Becker-Blease and Paul (2010) also found evidence for the effect attention to a stock has on the index inclusion effect when looking at S&P’s small- and mid-cap indices. Mase (2007) couldn’t find evidence for the attention hypothesis in the FTSE 100. This could be due to the mechanical nature of the rule-based FTSE 100, which causes additions to be less prevalent in news articles. On the other hand, Doeswijk (2005) found evidence supporting the attention hypothesis when looking at the Dutch Amsterdam Exchange Index (AEX), which is also a rule-based index.

2.5 Anticipation Hypothesis

The anticipation hypothesis is an attempt to explain any abnormal returns occurring before the announcement date. It states that since the index inclusion effect is a widely known anomaly, several investors will try to predict which stock will be incorporated into a widely followed index in order to buy the security before the announcement and profit from the price increase occurring after the announcement. The same can occur when looking at exclusion events. In this case, the investor shorts the security, which is expected to be deleted. The position will be closed after the announcement date to profit from the decrease in the price of the underlying value. This effect is particularly prominent for rule-based indices. Meaning, the criteria for inclusion and exclusion as well as the announcement dates and review timeframes are publicly known before they occur. Examples of such indices are the British FTSE 100 by the Financial Times, the Dutch AEX by Eurostoxx, or the American small-cap index Russell 2000. Petajisto (2011) was able to show significant abnormal returns before the announcement for the Russell 2000 index. Petajisto (2011) also looked at abnormal returns for the S&P 500 and shows abnormal returns before announcement for both inclusions and exclusions, whereas abnormal returns for exclusions are higher. It is not apparent from his results, how significant the abnormal returns are. Elliott (2006) showed low abnormal returns for the S&P 500 of 0.53% and 0.69% for 10 and 5 days before the announcement respectively. Both are statistically significant. Earlier results by Jain (1987) and Harris and Gruel (1986) show no such preannouncement abnormal returns for the S&P 500.

2.6 Influence of ETFs

Since their inception in 1993, ETFs have played a continuously growing role in the index investing world. According to Seyffart (2021), passive investing overtook the U.S. equity market in 2018, that was dominated by active investors. In 2021, passive investors owned 53.8% of the U.S. market. This begs the question of how ETFs could have influenced the index inclusion effect. It is important to understand some of the basic principles surrounding ETFs, in order to evaluate their impact on the index inclusion effect. According to Liebi (2020), there are two types of ETFs: physical and synthetic. Physical ETFs are comprised of actual securities, whereas synthetic ETFs use total return swaps to replicate the index price. Most ETFs are physical. They both have a primary and a secondary market. In the primary market, an ETF provider like Blackrock creates ETF shares, which are exchanged for underlying securities that make up an index. An authorized participant (AP), such as J.P. Morgan, provides the securities in exchange for newly issued ETF shares. The AP can now hold the ETF shares or sell them on the secondary market. This makes it possible for ETF prices to be very close to their net asset value (NAV). If the ETF trades above its NAV, the AP can buy the underlying securities and sell them to the ETF provider. Those newly acquired ETF shares can then be sold for a profit on the secondary market. If the ETF trades below its NAV, the AP can buy ETF shares on the secondary market and exchange them for the underlying securities with the ETF provider. The newly acquired securities can then be sold for a profit. This arbitrage causes the ETF price to closely track the NAV. According to Ben-David et al. (2018), this statistical arbitrage accounts for 50% of the trade volume in the SPDR, the biggest index ETF for the S&P 500.

This gives rise to two interesting effects that ETFs have on their underlying securities. The first one is the price discovery theory. It states that when a fundamental shock occurs, the ETF price reacts first, and through arbitrage, the underlying stocks align with the new equilibrium. This should, in theory, have a positive effect on price discovery. The second theory, called the liquidity trading hypothesis, states that when a non-fundamental shock occurs, the ETF price reacts first, and arbitrage causes the NAV to align with the ETF in an equilibrium different from the fundamental value. In the long run, both the ETF and the NAV will align again at fundamental values afterwards. This should cause higher volatility for securities included in indices followed by ETFs and have a negative impact on their price discovery. There have been studies supporting both theories. Studies supporting the price discovery hypothesis include Madhavan and Sobczyk (2016), Glosten et al. (2016), and Lettau and Madhavan (2018). There have been other studies disagreeing with the price discovery hypothesis, such as Israeli et al. (2017). But also those that support the liquidity trading hypothesis, such as Ben-David et al. (2018) and Wang and Xu (2019). Liebi (2020) makes the case that both hypotheses coexist. Meaning, ETFs provide a net increase in price discovery but also increase volatility. Another way price discovery seems to be improved through ETFs, is their use as a cheaper alternative to shorting securities, as was shown by Li and Zhu (2018).

The relationship between ETFs and their impact on the index inclusion effect have been sparsely studied. One such study includes Mecca (2020). He looked at how the increase in ETF coverage of the S&P 500 affected the index inclusion effect between 1993 and 2021. In Mecca's study ETF coverage is "derived by taking the total market cap of the S&P 500 index and calculating the proportion of the top three S&P 500 market cap weighted ETFs' market cap". He found that with each percent increase in ETF market cap, the abnormal returns decreased by 1.4%. He also showed evidence suggesting that ETFs decrease the amplitude but also the permanence of the index inclusion effect in the S&P 500.

According to Hegde and McDermot (2004), Boehmer and Boehmer (2003), Richie and Madura (2007), as well as Marshall et al. (2015), ETFs have increased the liquidity of stocks that are part of indices. This could in turn show the importance of the liquidity hypothesis as an explanation for the index inclusion effect.

2.7 Impact of Firm Size

Looking at the importance of firm size, there is only limited research available. Becker-Blease and Paul (2010) looked at differences in abnormal returns between the S&P MidCap 400 and the S&P SmallCap 600 indices. They find that stocks added to the “MidCap” index show a permanent increase in value of 3.14% (3.82%), and stocks added to the “SmallCap” have mean (median) permanent price revisions of 1.96% (3.01%). They also found the main explanation for the existence of the effect in smaller companies is the liquidity effect. The problem with the study is the time frame used. The data was collected from 1996 until 2003, long before passive investors overtook active investors in the U.S. equity market. This could mean that there has been a change in the importance of firm size for the inclusion effect in a more recent time frame. A more recent study conducted by Kaptein (2016) looked at the differences in abnormal returns for stocks added and deleted to the Dutch indices ranked by market cap AEX, AMX, and AscX from 1994 until 2015. Kaptein found significant abnormal returns for both the large-cap index (AEX) and the mid-cap index (AMX), but not for the small-cap index (AscX). He also found the effect to quickly reverse for the AEX and to be permanent for the AMX. These results, however, should be taken with a grain of salt since they looked at a rule-based index. The chosen indices published by Euronext have a very clear ruleset and schedule for including and excluding stocks, leading to more investors already anticipating changes in composition. The second problem is the low coverage of these indices by the passive investing world, making it harder to compare with more prominent indices from S&P. Lastly, the time frame leads back until 1994, therefore including behavior before the dominance of passive investors.

2.8 Limits to Arbitrage

Even though ETFs might have made markets more efficient, there are still factors that limit arbitrage for the IIE. Three of these were formulated by Shleifer and Vishny (1997). Namely, noise risk, fundamental risk, and transaction costs. An arbitrageur could run the risk of the underlying asset increasing further in price for an addition when shorting in an effort to profit from a price reversal. It is also hard to find a perfect substitute for the asset in order to hedge risks, although ETFs can reduce that risk like Li and Zhu (2016) showed. This is called the fundamental risk. Noise risk arises when the mispricing can increase even more and for a longer time, which could force the arbitrageur to close a short position prematurely. Transaction costs are in this case mitigated due to the low costs of ETFs, including inverse ETFs, in order to short an index.

3. Hypotheses

The objectives of this thesis are to see if the index inclusion effect is still prevalent since ETFs took over, how ETFs influence the index inclusion effect, and if there is a difference in firm size. I will look at the total of the S&P 1500 (large-, mid-, small-cap indices combined) which shows a wider range of ETF market share numbers. The following hypotheses are formulated:

H1: *ETF coverage at the time of inclusion (exclusion), correlates positively (negatively) with the amount of abnormal returns observed after the announcement date.*

The reason why I predict this relation is that I think higher coverage by ETFs should cause bigger short-term demand shocks to the included and excluded stocks. This should in turn increase the equilibrium price for the stocks as the demand curve shifts to the right. This also indirectly assumes that the downward sloping demand curve hypothesis holds true. The motivation is that, when looking at the current state of the literature, it seems like the DSDCH is likely true. Given my assumption of DSDCH, I also expect the following:

H2: *The inclusion (exclusion) to an index will result in positive (negative) abnormal returns after the announcement.*

This is the expected result when looking at virtually all previous studies that have been conducted on the index inclusion effect. It will be interesting to see if the effect differs in amplitude and permanence from previous findings. It could also be the case that the increase in market efficiency caused by ETFs has made the inclusion effect a non-event. I predict this not to be the case, as other previously mentioned literature in Section 2.6 has also shown evidence that supports the opposite effect of ETFs.

H3: *Firm size correlates negatively (positively) with abnormal returns after the announcement for inclusions (exclusions).*

I expect the correlation with firm size to be negative since I found that the small-cap index has a proportionally bigger ETF coverage than the larger indices. ETF coverage refers to the sum of the market values of all ETFs tracking an index divided by the sum of the market caps of all companies the tracked index is comprised of. The higher coverage will cause bigger spikes in stock prices since proportionally more stocks will have to be bought by the ETF providers. Another reason I predict this outcome is the existing evidence for the liquidity and attention hypotheses. The impact of new liquidity and attention should be proportionally higher for smaller companies since they are far lesser known and have lesser liquidity compared to already larger, more traded, and more prominent companies.

4. Methodology

An event study is used order to determine if abnormal returns are present around the announcement date for index changes. The same event study will also be used to look at the differences for firm sizes, i.e. the three different market cap indices. Further, a linear and nonlinear regression analysis will be performed to determine if ETF coverage or firm size have an influence on the index inclusion effect.

4.1 Event Study

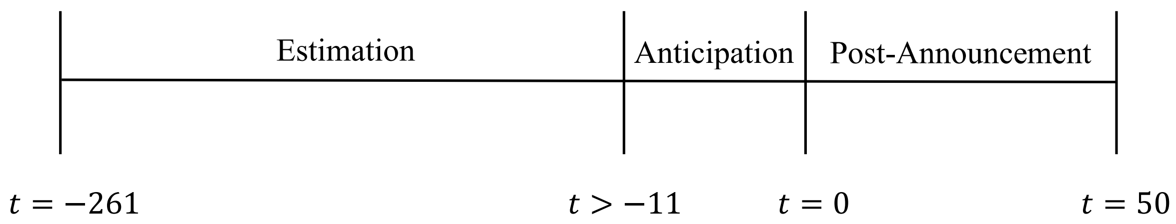
Developed by Fama et al. (1970), the event study is the most frequently used method to determine if an index event creates abnormal returns. This methodology first estimates an expected return by using the market model and then compares it to the actual return that can be observed. The difference yields the abnormal return. According to Brown and Warner (1985) and Edmister, Graham and Pirie (1994), the market model provides a higher power compared to the mean adjusted and parameter-based models when event clustering is present. The market model takes the beta of each individual stock and multiplies it with the market return of a market-cap weighted market portfolio. The abnormal return for share i at time t is therefore as follows:

$$\alpha_{it} = R_{it} - \beta_i R_{mt}$$

α_{it}	Abnormal return of stock i at time t
R_{it}	Return of stock i at time t
R_{mt}	Return of market-cap weighted market portfolio
β_i	$\frac{cov(R_{it}, R_{mt})}{var(R_{mt})}$

I will then aggregate all the observed abnormal returns over a specified timeline which then shows the cumulative abnormal average return (CAAR) each day and plot them over time for the inclusions and exclusions for each index.

To find a trend in the movement of the CAAR over time, a timeline has to be developed. First, I will use the announcement date as the day where $t = 0$, and use $t = -10$ and $t = 50$ to look at a potential anticipation effect before the announcement and to see if the effect is permanent after the announcement. If it is not permanent, we will see how long it takes on average for the inclusion effect to reverse. To determine the expected return for stock i, the daily returns occurring from $t = -261$ until $t = -11$ will be used as the estimation timeframe, which equates to a time frame of one year. The timeline looks as follows:



The results will then be tested for their significance using a t-test. It tests if the mean of the results is significantly different from the predicted mean. In this case, the predicted mean is zero. For the test to be valid, the population should be normally distributed, and the returns need to be independent (uncorrelated). The price data as well as the data on leavers and joiners from indices were taken from Refinitiv. The data includes the deletions and additions for the S&P 500, S&P MidCap 400, and S&P SmallCap 600 from 2012 until 2019. Additions to the two latter indices that are a result of a demotion from a bigger index will not be counted as additions. Deletions resulting from a merger or delisting will be excluded from the data set. Because Refinitiv, Bloomberg, and CompStat only provide the implementation dates and not the announcement dates, and because S&P Global has heavily restricted the excess to the announcement dates since July 2020, the announcement dates had to be manually retrieved from S&P Global's press release page. The event study was conducted using the event study tool provided by Wharton Research Data Services (WRDS). It only allowed the use of data up until December 31st 2019.

4.2 Regression Analysis

A linear regression analysis will be performed in order to test H1 and H3. The obtained abnormal return for stock i from $t = 0$ until $t = 1$ will be the dependent variable (DV) for all regressions performed. The ETF coverage of the index in question on the day of the announcement will act as the independent variable (IV) for testing the importance of ETF coverage for abnormal returns. The market capitalization in the month of stock being included or excluded is used as the IV for testing the importance of firm size on abnormal returns. Due to both IVs having a large discrepancy in data points when combining all three indices, the log to the base of 10 will be taken to normalize the data for the aggregate of all indices, the "S&P 1500". This results in the following equation:

$$DV = \alpha + \beta * IV$$

α Y-axis intercept

β linear relationship between DV and IV

Since I am not aware of an exact measure for the ETF share of each of the three indices in question for the determined time frame, an alternative proxy variable had to be found. In order to determine the ETF market share of each index, the 12 biggest ETFs for the S&P 500 and S&P 400 each and the 8 biggest ETFs for the S&P 600 have been used. This does not represent the exact ETF market share for each index, but is an extremely close approximation. They almost always represented more than 90% of the total market value of all ETFs covering each index.

4.3 S&P Indices

In order to determine a difference in firm size when looking at the index inclusion effect, I will use the three market-cap-based indices provided by Standard & Poor's. The S&P 500 represents large-cap firms in the study. The index is comprised of the 500 largest U.S. companies that are publicly listed. In absolute numbers, it is one of the most followed equity indices in history. It is also the most commonly used index to analyze the index inclusion effect.

The S&P MidCap 400 (S&P 400) index will represent mid-cap companies, as the name already suggests, and is made up of the next 400 biggest companies below the S&P 500. Deletions from the S&P 400 can either be caused by a delisting, merger, promotion to the S&P

500, or demotion to the S&P SmallCap 600 (S&P 600). Securities that are deleted from the S&P 500 will be directly added to the S&P 400 if the deletion did not occur due to a delisting or merger.

The S&P SmallCap 600 index will represent small-cap companies. It is comprised of the 600 next-biggest companies preceding the S&P 400 and S&P 500. The same conventions of the S&P 400 can be applied to the S&P 600.

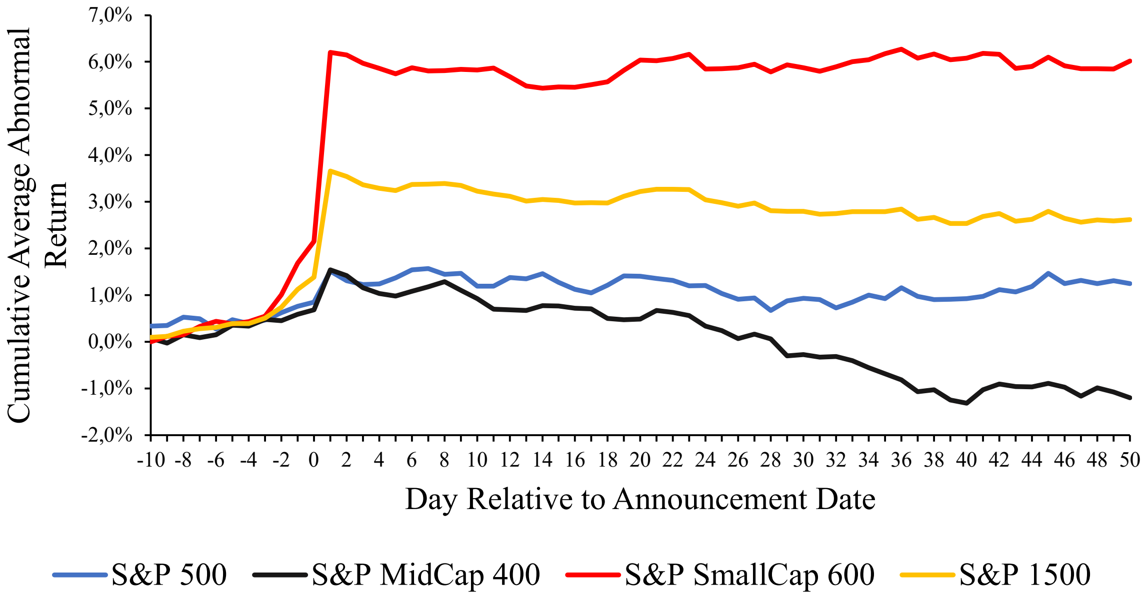
According to S&P Global, these indices do not select stocks using a rule-based methodology. The index committee of S&P determines which stocks are selected based on eligibility criteria such as domicile, exchange listing, market capitalization, investable weight factor, liquidity, and financial viability. Changes to composition are announced at 05:15 p.m. Eastern Time on www.spglobal.com. There is no specific date on which they are announced, making it hard to predict changes to the composition of one of the three indices.

5. Results

This section presents the results of the event study and the regressions in order to test the three hypotheses mentioned in Section 3. The results will be divided by inclusion and exclusion for each of the event studies and the regressions. The inclusions and exclusions will be categorized by the three indices and the aggregate of them, which will be called "S&P 1500".

5.1 Event Study Inclusions

Figure I Cumulative Average Abnormal Returns for Inclusions



5.1.1 S&P 500

Table I Cumulative Abnormal Returns for Inclusions of the S&P 500

Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	0,85%	**	2,6073	0,0101	149
(-5,0)	0,58%		1,4943	0,1372	149
AD+1	**0,66%**	***	2,7689	0,0063	149
(+1,+6)	0,69%	***	2,9062	0,0042	149
(+1,+11)	0,34%	*	1,7517	0,0820	149
(+1,+50)	0,39%		1,2436	0,2157	149

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The following tables depicting the results of the event study show the different CAARs for different timeframes. “AD+1” indicates the abnormal return one day after the announcement day. This day has been chosen because, as mentioned in Section 4.3, changes to indices are announced at 05:15 pm Eastern Time and therefore after market close. The reactions to the announcement therefore only become apparent on the next day. The timeframes "-10,0" and "-5,0" are used to check for a pattern in any abnormal returns occurring before the announcement. The timeframes after the announcement days all include the abnormal return of AD+1 to see how long it takes for the abnormal return caused by the announcement to reverse. If the CAAR is equal to zero again, the abnormal returns caused by the inclusion or exclusion have reversed back to where they were before.

When looking at the results for the S&P 500, Table I shows a statistically significant mean abnormal return on the day after the announcement date (AD+1) of 0,66%. Interestingly, there is also a statistically significant cumulative average abnormal return (CAAR) of 0,85% from 10 days before the AD until the AD. This result supports the existence of an anticipation effect. Although only of marginal amplitude, this is in line with previous findings by Elliott (2006) and Patejisto (2011). The abnormal returns after 50 days (including AD+1) are not significant, suggesting that the effect is temporary. The results are also in line with Mecca's findings, which showed a similar small abnormal return, making the index inclusion effect almost a non-event.

5.1.2 S&P MidCap 400

Table II Cumulative Abnormal Returns for Inclusions of the S&P MidCap 400

Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	0,69%		0,6729	0,5016	241
(-5,0)	0,53%		1,1696	0,2433	241
AD+1	**0,86%**	***	**4,6111**	**0,0000**	**241**
(+1,+6)	0,39%	**	2,2822	0,0234	241
(+1,+11)	0,01%		1,2944	0,1968	241
(+1,+50)	-1,89%		-1,1744	0,2414	241

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The story is similar for the mid-cap index. Showing only a statistically significant abnormal return one day after the AD of 0,86%. The main difference in the S&P 500 is the reversion of the effect. After 11 days, the effect seems to disappear as the results become insignificant. There also seems to be no significant anticipation effect compared to the S&P 500. Overall, the results for the S&P 400 would support the price pressure hypothesis.

5.1.3 S&P SmallCap 600

Table III Cumulative Abnormal Returns for Inclusions of the S&P SmallCap 600

Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	2,15%		0,0225	0,9821	326
(-5,0)	1,71%		1,2604	0,2084	326
AD+1	**4,05%**	***	**17,6388**	**0,0000**	**326**
(+1,+6)	3,73%	***	10,3889	0,0000	326
(+1,+11)	3,72%	***	9,2651	0,0000	326
(+1,+50)	3,87%	***	5,9538	0,0000	326

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The small-cap index seems to show the biggest significant abnormal returns of 4,05% one day after AD. This is vastly different compared to the two bigger indices. The effect is also not showing any signs of reversion, remaining at 3,87% after 50 days. This supports the downward sloping demand curve hypothesis. It also supports the liquidity hypothesis since small-cap companies are affected more by the change in liquidity that is caused by being added to a widely followed index. Although there are studies supporting the DSDCH, none of them have looked at the S&P 600 so far. No significant anticipation effect can be observed. When looking at Figure I, it is clear that the S&P 600 shows the biggest difference to the rest of the tested indices. This could be caused by either firm size or ETF coverage and will be tested for in the regression analysis.

5.1.4 S&P 1500

Table IV Cumulative Abnormal Returns for Inclusions of the S&P 1500

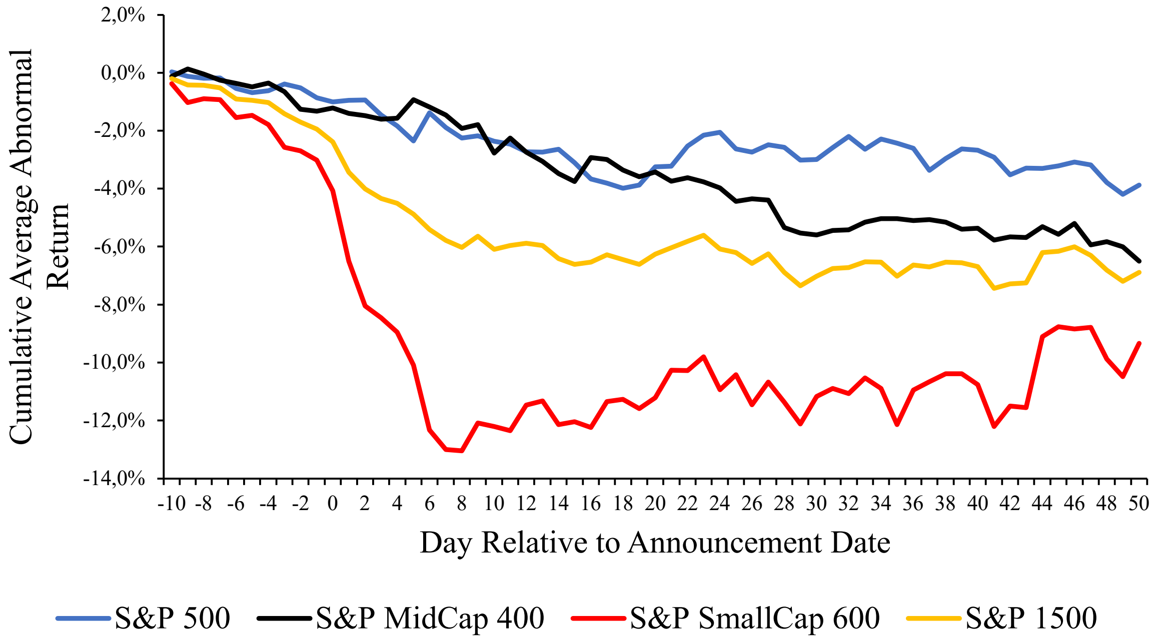
Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	1,39%		1,3991	0,1622	716
(-5,0)	1,08%	**	2,1298	0,0335	716
AD+1	**2,27%**	***	**15,6693**	**0,0000**	**716**
(+1,+6)	1,98%	***	10,0879	0,0000	716
(+1,+11)	1,78%	***	8,3289	0,0000	716
(+1,+50)	1,23%	***	4,1824	0,0000	716

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Looking at the aggregate of all three market-cap indices, a statistically significant abnormal return of 2,27% one day after AD can be found. The effect does not reverse 50 days after the AD, indicating that the demand curve has a downward slope and that the new liquidity provided by the inclusion to a widely followed index has reduced the expected return which in turn causes an increase in stock price. There is no previous study that has analyzed the index inclusion effect when looking at the S&P 1500, making it hard to see how the effect has changed over time as this event study only covers inclusions from 2012 until 2019. The results show a significant anticipation effect of 1,08% for the 5 days preceding the announcement date. Overall, the results show that the reasons for the existence of the IIE effect seem to vary widely between the three selected indices. But it can be said that by looking at the results, the IIE is still present, independent of firm size and ETF coverage. The results seem to confirm Hypothesis 2 as well as Hypothesis 3. H2 because all indices show abnormal returns after the announcement, and H3 because as market-cap decreases, the abnormal returns increase. One could also argue that it supports H1, since the small-cap index shows the highest abnormal returns and has by far the highest ETF coverage of all three indices (around 14% compared to around 3% ETF coverage). This will become more apparent in the regression analyses.

5.2 Event Study Exclusions

Figure II Cumulative Average Abnormal Returns for Exclusions



5.2.1 S&P 500

Table V Cumulative Abnormal Returns for Exclusions of the S&P 500

Event Day	Mean	T-Statistic	P-Value	Number of observations
(-10,0)	-1,00%	0,2735	0,7848	157
(-5,0)	-0,46%	-1,5595	0,1209	157
AD+1	**0,19%**	**1,1483**	**0,2527**	**157**
(+1,+6)	-0,38%	-1,2297	0,2222	157
(+1,+11)	-1,46% *	-1,8624	0,0661	157
(+1,+50)	-2,88%	-1,4270	0,1577	157

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

There are no significant results for the exclusions from the S&P 500. Figure I shows even a positive cumulative abnormal return of 0,19% one day after AD, but the result is statistically insignificant. After 50 days, the CAAR is -2,88% but not statistically significant. The only marginally significant result is the CAAR of -1,46% 11 days after AD. Mecca (2020) could also not find any significant results for the exclusions in the 2010s and 2020s for the S&P 500.

5.2.2 S&P MidCap 400

Table VI Cumulative Abnormal Returns for Exclusions of the S&P MidCap 400

Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	-1,22%		-0,9439	0,3461	249
(-5,0)	-0,86%		-1,0245	0,3066	249
AD+1	**-0,12%**		**-0,4798**	**0,6318**	**249**
(+1,+6)	0,03%		-0,8564	0,3933	249
(+1,+11)	-1,03%		-1,3401	0,1826	249
(+1,+50)	-5,28%	**	-2,5423	0,0123	249

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The mid-cap index showed an insignificant abnormal return one day after AD of -0,12% indicating the IIE plays no significant role. In contrast to the S&P 500, a significant negative CAAR of -5,28% can be observed for the 50 days following the announcement date. This could indicate that there is a sell off or shorting caused by the announcement but several days later. It could be the case that the implementation date plays a bigger role for exclusions than it does for inclusions. On average, the implementation of a change in index composition happens 5 days after the announcement, according to Mecca (2020). This could explain the delay in the observed abnormal returns. Another interpretation of the lack of a high and significant change in abnormal returns right after the announcement is that ETF providers spread out small-cap sell-offs in order the reduce the increased price impact a single sell-off would have compared to large-caps. The same cannot be observed for additions because the ETF providers need to buy the newly added stocks as soon as possible in order to track the index price if the ETF is a physical one. If a stock gets excluded from an index, the ETF can still own it while tracking the index closely.

5.2.3 S&P SmallCap 600

Table VII Cumulative Abnormal Returns for Exclusions of the S&P SmallCap 600

Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	-4,08%	**	-2,0343	0,0428	300
(-5,0)	-2,53%	**	-2,5523	0,0112	300
AD+1	**-2,19%**	***	**-5,1588**	**0,0000**	**300**
(+1,+6)	-8,25%	***	-6,1325	0,0000	300
(+1,+11)	-8,28%	***	-4,6686	0,0000	300
(+1,+50)	-5,26%	**	-2,3557	0,0202	300

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The small-cap index shows different results compared to the two bigger indices. There is a clear negative abnormal return of -2,19% observed one day after AD. The result is also statistically significant. The CAAR seems to increase with time, showing a CAAR of -8,25% just five days after AD, -8,28% 10 days after AD, and -5,26% 50 days after AD. All results are statistically significant. The further decrease in abnormal returns after the announcement could be another sign that the implementation date is of greater importance for exclusions and that ETF providers gradually sell off the excluded shares. The permanence of the effect supports the downward sloping demand curve hypothesis as well as the liquidity affect. Abnormal returns can also be observed in the days before the announcement. -4,08% for 10 days before AD and -2,53% 5 days before AD. This could also indicate that the exclusion is a result of decreasing company performance instead of an anticipation effect. It could also mean that more effort is being put into predicting changes in composition for the small-cap index since the lower liquidity for the small-cap companies increases the magnitude of the abnormal returns occurring after the announcement for both deletions and additions. Both show higher differences in abnormal returns before the announcement compared to the S&P 500 and S&P 400.

5.2.4 S&P 1500

Table VIII Cumulative Abnormal Returns for Exclusions of the S&P 1500

Event Day	Mean		T-Statistic	P-Value	Number of observations
(-10,0)	-2,39%	**	-2,0613	0,0396	706
(-5,0)	-1,48%	***	-3,0365	0,0025	706
AD+1	**-0,91%**	***	**-4,4284**	**0,0000**	**706**
(+1,+6)	-3,03%	***	-5,4100	0,0000	706
(+1,+11)	-3,58%	***	-4,8432	0,0000	706
(+1,+50)	-4,50%	***	-3,6779	0,0003	706

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

The aggregate of all three indices shows similar behavior to the S&P 600. The difference being in the reduced magnitude of the effects. A statistically significant abnormal return of -0,91% can be observed. The effect seems to increase after the announcement, just like all the other three indices. The CAAR for five days after AD+1 is -3,03%, for ten days after AD+1 -3,58% and for fifty days after AD+1 -4,50%. These results are also statistically significant. The increase in abnormal returns after AD could again indicate the importance of the implementation date instead of the announcement date and the gradual sell-off by ETF providers described previously. Just like the S&P 600, significant CAARs can be observed before the announcement date. -2,39% and -1,48% for ten days and five days before AD, respectively. The results seem to support Hypothesis H3 but are mixed for H2. They support H3 because, as market cap decreases, the abnormal return after the announcement increases. They partially support H2, because only the S&P 1500 and S&P 600 show statistically significant abnormal results after announcement. Overall, the S&P 500 and 400 indices show similar behavior, and the S&P 600 sticks out with its different results, as is the case when looking at the deletions. This difference could support Hypothesis 1 since the S&P 600 has the highest ETF coverage and the most negative abnormal returns. The results of the event study seem to only partially support Hypothesis 2, as only the small cap and aggregate index show significant abnormal returns after announcement. Hypothesis 3 cannot be fully supported by the results, since the observed positive correlation between firm size, i.e. index market cap, and abnormal returns for the exclusions are not all statistically significant.

5.3 ETF Coverage Regression Analysis

5.3.1 Inclusions

Table IX ETF Coverage Regression Results for Inclusions

Regression	Coefficient	Estimate		Std. Error	T-Statistic	P-Value	R^2
R1500+ Log (ETF)	Intercept	0,0962	***	0,0083	11,6505	0,0000	0,0964
	Log (IV)	0,0522	***	0,0060	8,7261	0,0000	
R500+_ETF	Intercept	0,0516	***	0,0140	3,6740	0,0003	0,0650
	IV	-2,1691	***	0,6786	-3,1963	0,0017	
R400+_ETF	Intercept	0,0506	***	0,0092	5,5177	0,0000	0,0808
	IV	-1,0136	***	0,2212	-4,5831	0,0000	
R600+_ETF	Intercept	0,0327	***	0,0063	5,2090	0,0000	0,0145
	IV	0,1651	**	0,0757	2,1796	0,0300	

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

When looking at the results of the regression analysis, there seems to be a clear connection between the amplitude of abnormal returns after the announcement and the amount of coverage an index has by ETFs. For inclusions to the S&P 1500, ETF coverage seems to explain 9,64% of the variance in abnormal return one day after the announcement. The result is statistically significant. The relation between ETF coverage and abnormal return is positive. This is the direct opposite of the findings of Mecca (2020), who did a similar regression. The major differences are that he looked only at the S&P 500, he used only the top three ETFs covering the index, the abnormal returns used are not just for one day after the announcement and the ETF coverage is only generated for the year of inclusion, not for the same day as is the case for this thesis's regression. The second difference is not as important, as the three biggest ETFs still cover around 80% of all ETFs covering the S&P 500 combined.

When we now compare the results for the S&P 500, they seem to be in line with Mecca's results. Also showing a negative relation between ETF coverage and abnormal returns. But they only seem to explain 6,5% of the variance in abnormal returns compared to Mecca's 35,1%. This major discrepancy could again be caused by the aforementioned differences in the regressions performed.

The S&P 400 shows similar behavior to that observed in the S&P 500 but ETF coverage is explaining more of the variance. The ETF coverage explains 8,08% of the variance in abnormal returns. All results are statistically significant.

Similar to the index aggregate, the S&P 600 index shows a positive correlation between ETF coverage and abnormal returns after the announcement. The correlation is weak, with it being only 0,1202 (square root of R^2) and the independent variable only explaining 1,45% of the variance in abnormal returns. A reason for this drastically different result compared to the two other indices is the extremely high ETF coverage of the S&P 600 index. The maximum is around 14%, and only around 3% to 4% for the S&P 400 and S&P 500. In order to find an explanation in the different effects ETF coverage has on abnormal returns, a multiple linear regression will be performed in Section 5.5.

5.3.2 Exclusions

Table X ETF Coverage Regression Results for Exclusions

Regression	Coefficient	Estimate		Robust Std. Error	T-Statistic	P-Value	R^2
R1500-Log (ETF)	Intercept	-0,0763		0,0232	-4,0096	0,0001	0,0163
	Log (IV)	-0,0464	***	0,0148	-3,4185	0,0007	
R500-_ETF	Intercept	0,0058		0,0109	0,5188	0,6047	0,0016
	IV	-0,2686		0,5657	-0,4913	0,6239	
R400-_ETF	Intercept	-0,0415	***	0,0144	-3,0879	0,0022	0,0390
	IV	1,0574	***	0,3905	3,1649	0,0017	
R600-_ETF	Intercept	-0,0168		0,0135	-0,9107	0,3632	0,0023
	IV	-0,1860		0,1673	-0,8297	0,4074	

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

When looking at the exclusions, all indices show a negative relationship between abnormal returns and ETF coverage, except for the S&P 400. Only the results for the index aggregate and the S&P 400 are statistically significant. 1,63% and 3,90% of the variance for the S&P 1500 and S&P 400, respectively, can be explained by ETF coverage. It should be noted that the regression results for the exclusion are heteroscedastic. In order to test if the heteroscedasticity affects the coefficients, robust standard errors are used in Table X. They are calculated with the Huber-White method. For the statistically significant results, the robust standard errors indicate that the slope coefficients are far away from zero since all of them are several times the size of the robust standard error. This means the coefficients are still relevant and heteroscedasticity does not negatively affect the result's power.

5.4 Firm Size Regression Analysis

Figure III Firm Size Regression Results for S&P 1500 Additions

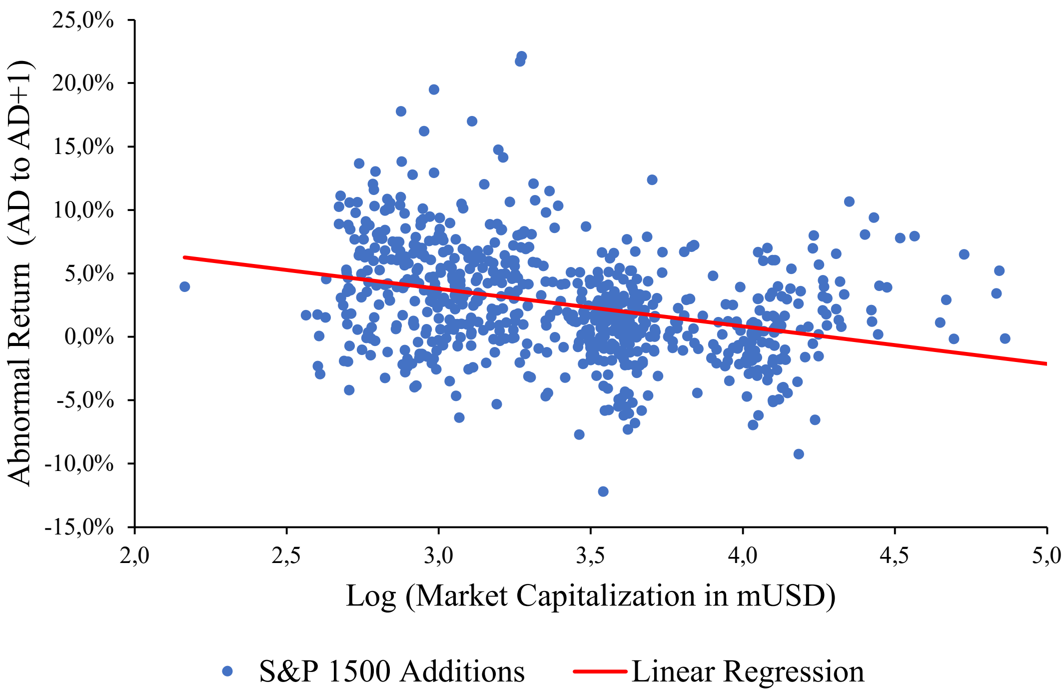


Figure IIV Firm Size Regression Results for S&P 1500 Deletions

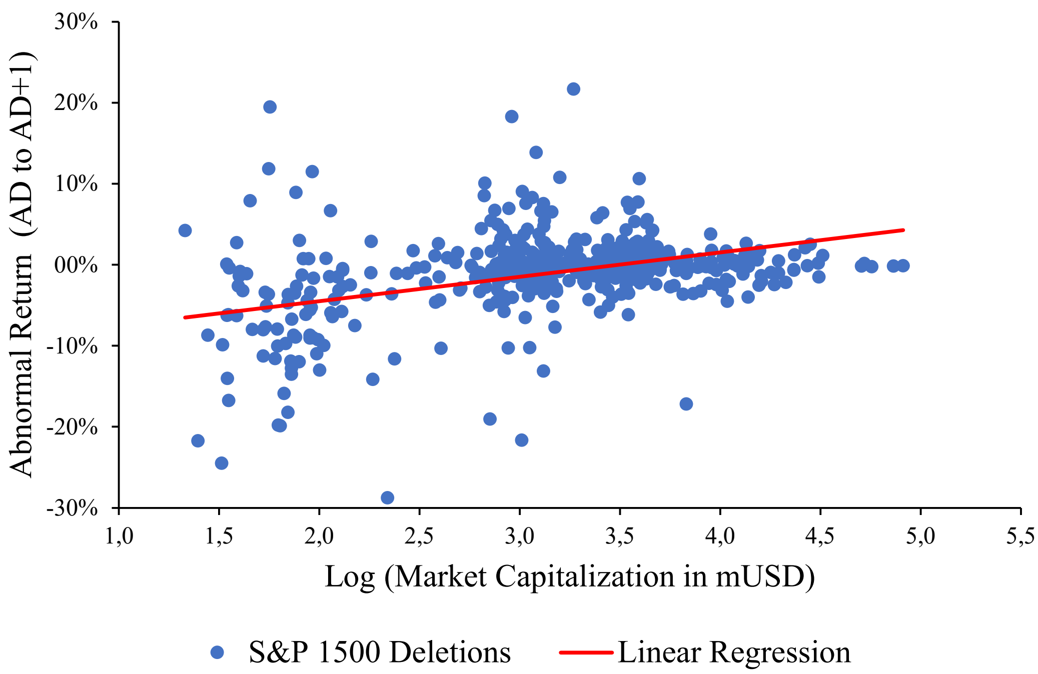


Table XI Firm Size Linear Regression Results for S&P 1500

Regression	Coefficient	Estimate		Std. Error	T-Statistic	P-Value	R^2
R1500+ Log (FS)	Intercept	0,1265	***	0,0108	11,6664	0,0000	0,1105
	Log (IV)	-0,0296	***	0,0031	-9,4188	0,0000	
R1500- Log (FS)	Intercept	-0,1049	***	0,0144	-7,2858	0,0000	0,0902
	Log (IV)	0,0301	***	0,0045	6,6801	0,0000	

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Looking at the linear regression for inclusions, it can be observed that firm size explains 11,05% of abnormal results occurring one day after the announcement. A negative relationship can be observed. Figure IV clearly shows the negative relationship that is present. There seems to be the exact opposite correlation between firm size and abnormal returns when it comes to exclusions. All results are statistically significant. This is in line with the observations from the first two event studies, which also showed higher abnormal returns for smaller companies for inclusions. Both regressions seem to support Hypothesis 3.

5.5 Multiple Regression Analysis

In order to identify the reason for the different correlations between ETF coverage and abnormal returns for the different indices, a multiple regression with two explanatory variables will be performed. The two independent variables will be the log of the market capitalization in the month of stock being included or excluded (IV1) and the log of the ETF coverage of the index in question on the day of the announcement (IV2). Both will be multiplied to analyze the interaction effect between the two variables. The dependent variable will be the abnormal returns as described in Section 4.2.

Table XII Multiple Regression Results for the S&P 1500

Regression	Coefficient	Estimate		Std. Error	T-Statistic	P-Value	R^2
R1500+ MR	Intercept	0,5333	***	0,0704	7,5717	0,0000	0,1631
	IV1 (MC)	-0,1430	***	0,0216	-6,6123	0,0000	
	IV2 (ETF)	0,3007	***	0,0480	6,2699	0,0000	
	IV1*IV2	-0,0823	***	0,0142	-5,8014	0,0000	
R1500- MR	Intercept	-0,2732	***	0,0532	-5,1352	0,0000	0,1078
	IV1 (MC)	0,0848	***	0,0177	4,7903	0,0000	
	IV2 (ETF)	-0,1502	***	0,0393	-3,8250	0,0001	
	IV1*IV2	0,0471	***	0,0125	3,7767	0,0002	

Table XII shows the interaction effect between firm size and ETF coverage (IV1*IV2) when looking at the abnormal returns occurring in the S&P 1500 after an addition (R1500+ MR) or deletion (R1500- MR). All results are statistically significant. The pattern for both deletions and additions seem to show some similarities. For additions, firm size has a negative effect and ETF coverage a positive effect on abnormal returns. The interaction between them also has a positive effect. The same can be observed for the deletions but with switched signs. This makes sense since for deletions, a negative sign indicates an increase in the magnitude of abnormal returns and a positive sign the opposite. The proportions of impact each coefficient has on abnormal returns are similar too. The ETF coverage coefficient is twice the firm size coefficient but in the opposite direction. The firm size coefficient is around twice the size of the interaction coefficient. This difference in impact of each of the variables could explain why ETF coverage had a negative impact on abnormal returns for additions to the S&P 500 and S&P 400 but a positive impact on the S&P 600 and S&P 1500. The regression shows that if a company reaches a sufficient firm size, the positive effect a higher ETF coverage has on abnormal returns can be neutralized or reversed due to the interaction effect taking place between firm size and ETF coverage.

6. Discussion and Conclusion

6.1 Summary of findings

The existence of the index inclusion effect for the S&P 500, 400, 600 and the aggregate of them named S&P 1500 has been proven by the results obtained by the event study. All indices show abnormal returns after announcement. The same cannot be said about the exclusions, as not all results were statistically significant. Only those for S&P 400 and the S&P 1500 were significant. H1 is therefore fully supported only when looking at inclusions.

The results of the event study have also shown a clear discrepancy between the biggest and smallest indices when it comes to abnormal returns after the announcement of an inclusion. Abnormal returns are significantly higher for smaller companies compared to larger ones when included, and vice versa when excluded. This indicates a negative relationship between firm size and abnormal returns for inclusions and a positive relationship for exclusions. The effect for the exclusions does not happen immediately like it does for the inclusions. That is also further reinforced by the findings of the regression performed where market capitalization is used as an independent variable to explain abnormal returns. The regression shows a negative linear relationship that explains 11,05% of the variance in abnormal returns occurring due to inclusion. The implementation date seems to be more important than the announcement date for exclusions, or ETF providers gradually sell off their shares to avoid large price changes, and or arbitrage is more difficult for exclusions. The results of both the event study and the regression analysis support Hypothesis 3.

ETF coverage seems to play a significant role in the amplitude of abnormal returns after the announcement. There is an interaction effect between firm size and ETF coverage that can cause the positive effect ETF coverage has on abnormal returns for additions to reverse into the negative for the largest stocks. This is observable for the S&P 500 and S&P 400 where due to the large market capitalization, the effect of ETF coverage gets reduced by firm size (or even reversed). For the S&P 600, the effect of new liquidity caused by the addition seems to be higher due to the smaller firm size.

6.2 Limitations & Recommendations for Future Research

Even though the results for the impact of firm size and ETF coverage on the inclusion effect seem to show clear evidence of their importance, the limitations of the results have to be accounted for as well.

First of all, due to the limitations of the WRDS event study tool, only data up until the 31st of December 2019 was usable. Initially, a ten-year time frame from 2012 until 2022 was planned. Therefore, some of the most recent inclusions and exclusions could not be used in the data. The data is still large enough, with over 1400 unique events, to find statistical relevance in them.

Second, the data for the announcement dates was almost impossible to find since S&P Global has restricted access to that data since July 2020. Therefore, I had to manually write down all announcement dates and match them manually with the inclusions and exclusions. There is a possibility that some announcement dates are incorrect or wrongly matched. However, when looking at Figures I and II, a clear change in the abnormal return pattern can be noticed right after the announcement. I am more worried about how genuine the pre-announcement abnormal returns are and if they are a result of manual errors.

A smaller and less impactful limitation to the results is the use of only the 8 to 12 biggest indices for each index as an indicator for ETF coverage. It therefore does not fully represent the exact ETF coverage at each time but is very close, at least representing 90% of all ETFs' assets under management at each time.

The same goes for the use of monthly market capitalization as an indicator for firm size. Using the monthly market capitalization data was less data intensive and still represents the size of a firm at the time of inclusion or exclusion realistically, as market capitalization does not drastically change in a maximum time discrepancy of 31 days.

The prominent presence of heteroskedasticity for exclusions in the performed regressions should also be looked into further. This seems to suggest that there are better variables explaining the existence of negative abnormal returns for exclusions than ETF coverage of firm size.

A recommendation for future research would be to find out why the ETF coverage levels for the S&P 600 are so extremely high and if this has any serious implications for how this affects market mechanisms for the underlying securities of the index.

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