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THE PRICE IMPACT OF S&P 500 AFFILIATION

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Abstract: We examine how abnormal returns and abnormal return determinants change when a company is added to S&P 500. Newly added companies experience a significant increase in abnormal returns around the announcement and addition dates. This increase is accompanied by an improvement in liquidity and a decrease in associated shadow cost. While before their addition, firm-specific abnormal returns can be explained by price impact, they are explained by changes in trading activity during the addition event. Additionally, companies with higher leverage ratios benefit more from index affiliation.

JEL Classification: G10, G12, G14,

Keywords: Index addition, index restructuring, stock addition, liquidity, abnormal returns

1. Introduction

The index anomaly gained academic attention over half a century ago. The first articles to analyze the impact of index reconstruction date back to the '80s, when authors were curious to capture and explain the effects affiliation with the S&P 500 Index might have on the added (or removed) stocks.

Most existing literature suggests that including a stock in the S&P 500 index can positively impact its price and increase synchronicity. Nonetheless, there is no consensus regarding the drivers of these effects.

We aim to see whether the *price pressure hypothesis* (Scholes, 1972) and the *investor awareness hypothesis* (market segmentation hypothesis (Merton, 1987)) can explain the increase in abnormal returns around the addition date as well as to capture whether the abnormal return determinants change once a company is included in the index.

We employ a combination of event study, multiple regression analysis, and difference in difference analysis over two estimation and one event window to: (1) confirm there is a change in the behavior of the analyzed stocks, (2) understand whether return creation during the event window can be explained through the price pressure or investor awareness lenses.

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2. Literature review

Schleifer (1986) was one of the pioneering studies in this area. The author analyzed the companies included in S&P 500 and noticed that, upon the announcement that a company *would become* an S&P 500 member, its abnormal returns went up (on average) by 2.8%. The author points out that the effect did not reverse for 60 days window.

Harris and Gurel (1986) examine prices and volumes surrounding the S&P 500 reconstruction events and find evidence supporting the price-pressure hypothesis. However, the authors mention that the prices reverse about two weeks after the event.

Jain (1987) extended Shleifer's (1986) study by including a sample of deletions from the S&P 500. The author confirms the presence of a price effect associated with the S&P 500 restructuring. He mentions that included companies registered an average 3.1% return on the first trading day after inclusion, with no price reversal over the next 60 trading days.

The S&P Committee began pre-announcing S&P 500 changes in October 1989. To see if this change in the information environment might have an impact on stock prices directly affected by the restructuring effect, Beneish & Whaley (1996) focus solely on the period post-1990. Their results suggest an even higher impact on abnormal returns – up to 7.2% between the announcement and the addition date. Unlike previous studies, Baneish & Whaley (1996) mention a price reversal around two weeks into the restructuring. They offer two possible arguments: (1) a higher return premium associated with affiliation to the S&P 500 and (2) speculative activity caused by the influx of new information to the market.

Brealey (2000) analyzes and compares the index effects using the FTSE All-Shares and the FTSE 100 indices. The author does not report any significant price impact after index addition. However, he mentions that index deletions were subject to negative abnormal returns.

Barberis et al. (2005) studied the co-movement between S&P 500 and the new additions. They report that the correlation between the stock and the index increases after the inclusion event, while the results are stronger for the post-2000s data. Unlike previous studies, authors find evidence suggesting that the co-movement captured is an effect of investor sentiment and market friction and has nothing to do with the company's fundamentals.

Becker-Blease & Paul (2008) study the impact external shocks might have on stock liquidity to highlight potential investment opportunities. Authors conclude that in the event of a stock restructuring (which they consider an external event to the company and a liquidity shock), there is a significant positive relationship between the liquidity of a stock and the investment decisions, which is consistent with the liquidity premium.

Petajisto (2011) analyzes the indexing premium from 1990 to 2005. The author compares a large cap index effect (S&P 500) and a small cap index effect (Russell 2000). He reports abnormal returns for companies from both indices; however, the impact was significantly higher for the large-cap index affiliates.

Kasch & Sarkar (2014) use a control sample. The authors report higher profits, positive momentum, and increased market value. In terms of co-movement, the authors conclude a short-term reversal. Additionally, they mention that the control and actual samples manifest similar behaviors regarding the market value and co-movement with the index.

3. Data and Methodology

a. The curious case of the S&P 500 addition rules

Unlike many benchmark indices (Russel 2000, Nikkei, or Topix), the S&P 500 Index does not follow a calendar reconstitution approach. Changes to the index are made on an as-needed basis (Liu, 2019), while the level of transparency associated with the restructuring decision is relatively low (Afego, 2017).

The addition and deletion decisions are taken by the S&P Index Committee and are somewhat subjective. The Committee should announce the change five days prior to the restructuring. However, sometime the Committee will only name the company to be added without disclosing the actual date. In such cases, the actual addition date can be as far as one month into the future. All the announcements are publicly available on the S&P Website[1] at the same time to the clients and affected companies alike.

Index additions are announced as a supplement to index deletions. According to Chen et al. (2004), nearly ¾ of all S&P 500 deletions are caused by mergers, acquisitions, and bankruptcy events. To maintain the number of constituent stocks at 500, the S&P Committee will select new constituents based on criteria such as the company's market value, liquidity, domicile, percentage of free-float shares, sector representation and financial viability. It is worth noting that the company is not required to meet all criteria to be included, as the final decision is left at the discretion of the Committee.

In theory, all the information pertinent to the selection criteria is publicly available and should be incorporated in prices if the stock market is efficient. As such, the restructuring event should not bear any new information. (Liu, 2019).

b. Sample

Using media sources (Google, S&P Web site), we gathered our sample of additions and deletions from 1994-2019. We identified 622 restructuring events, during which 1178 companies were either added or deleted from the S&P 500 index. We use Chen et al. (2004) sample for the pre-2000s data, which is available on the Journal of Finance webpage. We exclude companies involved in corporate actions, companies delisted in the year following the event day, and companies that were subject to both an addition and a deletion event in the same year[2]. Our final sample is comprised of 522 additions and 117 clean deletions.

We experiment with the addition and the actual event date but notice no material difference in results; to ensure consistency across data, we use the effective day as our event.[3]

Similar to Liu (2011) & Daya et al. (2012), we use a two-year sample period, with one year in each direction from the event, to minimize the possibility of unknowingly including another extrinsic event in our data sample.

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[1] More details available from: https://www.spglobal.com/spdji/en/indices/equity/sp-500/#news-research

[2] Additional screens (such as availability of return and volume data during the year prior and after the event) were employed.

[3] We do this because the announcement date is not always 5 days before the effective date, which could lead to distortions in data.

Given a small sample size for our deletions,[4] the remainder of this paper will focus on the additions.

c. Data

We collect daily data (price, volume, number of shares outstanding, number of shareholders, ROA, leverage etc.) for the sample firms using Datastream and Eikon platforms provided by Refinitiv. The S&P 500 index is used as the market, while S&P 500 sector indices are used as industry proxies. The Fama-French MKT, SMB & HML factors are retrieved from Prof. French's website.

d. Hypothesis

There are several hypotheses that aim to explain the price impact around an index reconstruction event.

While variate in terms of instruments used to describe the abnormal return generation around the addition event, they can be traced to one of the two underlying theories that state that the abnormal return around the event day is either: (1) demand based, or (2) information based.

In this study we focus on two hypothesis that aim to explain the short-term abnormal return creation. Namely, the price pressure and the investor awareness hypothesis.

According to Scholes (1972) the long-term demand is perfectly elastic, yet the short-term demand can have a downward sloping curve due to the excessive buy-sell pressures. We believe that after addition the S&P 500 Index companies will experience a significant positive abnormal return, that will reverse over longer time horizons.

Investor awareness hypothesis (Merton, 1987), states that investors will only trade in a sample of companies of which they are aware. As such, he/she will require an additional premium for not being fully diversified. We believe that, affiliation with the S&P 500 Index will improve company's visibility, which in turn will increase investors' awareness.

e. Methodology

To capture the dynamic of the S&P 500 restructuring event, two estimation windows were used to account for potential changes in risk exposure that might happen during our event[5]. Our pre-event estimation window is (-260, -31), and the post-event window is (+31, +260). We allow 30 trading days around the event to limit any potential speculative impact. As a robustness check, we use a second set of estimation windows (-260, -101), (+101, +260) consistent with Liu (2011).

The individual-level analysis is then followed by a multiple regression analysis in which we identify the pre-event and the post-event behaviors and study to which extent the abnormal returns during the two estimation windows can be explained through (i)liquidity and investor awareness.

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[4] Which is further reduced by some independent and control variables used (our final sample consists of 90 deletions)

[5] Using the ex-post event window (Liu, 2011) or combining the two windows (Sheleifer, 1986) does not significantly impact the results.

We conclude the study with a difference in difference analysis to estimate whether liquidity and investor awareness changes are responsible for the abnormal return during the event window.

4. Results

a. Changes in abnormal returns

We compute abnormal returns to see whether the index re-constructure event causes a price impact.

The abnormal returns are computed as Jensen's alpha from the market model (1). To address some of the critiques in Afego (2017), we also compute the abnormal returns from the extended market and industry[6] model and the Fama-French 3 factor model.

$$AR_i = R_i - \beta_i * R_m \quad (1)$$

We begin this section by documenting the price effects around the addition day. Results based on abnormal and cumulative abnormal returns for the addition event are presented in Table 1.

Results for the Market & Market-Industry Model are very similar. As such, we will only keep the Market model results going forward. The Fama-French 3 Factor model results are quite different, and we will keep them as a robustness check.

We notice that the cumulative abnormal returns are positive even 15 days pre-event, suggesting there was some market anticipation before the reconstruction event. Furthermore, abnormal returns for the -5 day (usually associated with the announcement day) are positive and significant, with a coefficient of 0.2%. However, we can see that the abnormal returns are even higher one day before the announcement proxy, which can signify speculative pressures pre-announcement.

The gradual increase in abnormal returns captured by all three abnormal return (AR) measures until the re-constructure event can indicate external price pressures. Chen et al. (2004) explain this behavior. They suggest that the pre-announcement can trigger speculative practices among arbitragers willing to profit from the indexer's restructuring moves.

About 72% of our sample scored positive abnormal returns the day after the announcement that cannot be explained by the market or the Fama-French 3-factor models. This can be a sign of an increasing demand from both indexers and arbitragers, reflecting in a short-term increase in price pressure. (Scholes, 1972; Harris & Gurel, 1986).

[6] Because until 2008 the Real Estate companies from S&P were reported as a part of the Financial sector, they are regresses against the S&P 500 Financials index.

Table 1.

MAR is the mean abnormal return computed as Jensen's alpha from the specified model. %AR is the percentage of companies that have non-negative abnormal returns during the analyzed day.

	MAR(%)			%AR>=0		
Day	Market Model	Market & Industry Model	Fama-French 3-Factor Model	Market Model	Market & Industry Model	Fama-French 3-Factor Model
-10	0.00%	-0.05%	0.26%	50%**	51%	55%***
-9	0.05%	0.07%	-0.08%	51%**	52%	49%**
-8	0.12%	0.13%	0.08%	54%***	55%	50%**
-7	0.07%	0.05%	0.26%	51%**	51%	57%***
-6	0.37%***	0.32%***	0.33%**	55%***	57%***	55%***
-5	0.22%*	0.23%*	0.21%	50%**	55%	51%**
-4	0.30%***	0.30%***	0.34%***	72%***	72%	51%**
-3	0.27%**	0.26%**	0.58%***	52%**	53%	56%***
-2	0.41%***	0.45%***	0.24%	56%***	58%	48%**
-1	0.47%***	0.43%***	0.49%***	52%**	53%	54%**
Event Day	*0.25%***	*0.28%***	*-0.22%****	*53%**	*53%***	*45%****
1	-0.05%**	-0.03%**	-0.15%	48%	51%	45%***
2	0.02%**	-0.11%**	0.08%	50%	48%*	50%**
3	0.13%**	0.10%***	-0.18%*	53%	54%	41%***
4	0.01%**	0.04%**	-0.15%	53%	52%	50%**
5	0.14%**	0.16%**	-0.07%	52%	52%	47%***
CAR						
(-15, -6)				0.71%***	0.69%*	1.68%***
(-5, +10)				2.29% •	2.29% •	1.90%***
(-3, +10)				0.81%***	1.89%***	0.37%***
(+1, +10)				0.74%***	0.74%***	-0.70%

t-test (sign test) was used to test the significance of the mean, and the binomial distribution was used to test the significance for %AR>0 (as in Schleifer (1986), Chen et al. (2004).
***, **, * represents significance at 1%, 5% and 10% respectively.

Following Chakrabarti et al. (2005) we analyze the cumulative abnormal returns over a collection of windows ten days before the announcement and going ten days past the effective day. The values for the post-addition and pre-announcement windows are comparable, suggesting that the returns will likely reverse over a longer timeframe, which is consistent with the price pressure hypothesis.

b. Information quality & liquidity

The previous section confirms that index affiliation can impact abnormal returns, leading to a permanent (yet marginal) increase in abnormal returns while also causing a consistent (yet marginally significant) increase over the shorter event window. Nevertheless, the question regarding possible explanations of this effect remains unanswered.

To address this issue, we compute several proxies, as suggested by the academic literature[7], to test for the impact of liquidity and investor awareness on abnormal return generation around index restructuring.

The liquidity hypothesis

An increase in stock illiquidity should lead to an increase in prices, as explained in Amihud & Mendelson (1986), due to the illiquidity premium demanded by investors for trading in less liquid stocks.

We expect that liquidity will increase during the event window due to the lower transparency levels regarding the selection criteria. This will happen due to rising indexer demand (Chen et al. 2004) and speculative pressures.

To capture liquidity, we use four proxies to capture different liquidity characteristics. This approach will serve two purposes: (1) to be a robustness test and (2) to help us capture the dynamics of the re-constructure event.

Amihud's illiquidity measure (2002), which captures the price impact, is computed using the formula in eq. (2), $R^i_{t,d}$ is the return of the stock i on the day d, over the t window, while $V^i_{t,d}$ is the dollar volume.

$$ILLIQ^i_t = \frac{1}{Days^i_t} \sum_{d=1}^{Days^i_t} \frac{|R^i_{t,d}|}{V^i_{t,d}} \quad (2)$$

Zeros is the ratio of zero trading days over the total trading days, as suggested by Lesmond et al. (1999). It is a proxy for trading costs.
We computed the implicit Bid-Ask spread (Roll, 1984) using Goyenko et al. (2009) updated formula:

$$BidAsk_t = \begin{cases} 2\sqrt[2]{-cov(r_t, r_{t-1})} & \text{when } cov(r_t, r_{t-1}) < 0 \\ 0 & \text{when } cov(r_t, r_{t-1}) \geq 0 \end{cases} \quad (3)$$

All those three measures are proxies for illiquidity; as such, their increase should be a sign of liquidity worsening.

We also compute Turnover, the ratio between trading volume and number of outstanding shares. This is a direct measure of liquidity, the only one we use that can capture liquidity without information production (Chen et al. 2004).

We calculate each measure for pre- and post-estimation windows and test the difference between the means for the two windows using the t-test and the non-parametric Mann-Whitney[8] test.

Results from Table 2 suggest a significant positive change in Turnover post-addition and a significant negative change in illiquidity as captured by the Amihud measure. Results for Zeros and the implicit bid-ask spread are inconclusive.

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[7] To name a few: Chen et al. (2004) use Amihud's illiquidity to explain abnormal returns, Daya et al. (2012) use Bid-Ask spread to capture changes in trading activity, Baran & King (2012) use Turnover to explain the cost of capital.

[8] Armitage et al. (2002) offer a detailed description of the two tests.

Investor awareness hypothesis

Measuring the impact of investor awareness has proven to be a complex task, primarily due to the lack of a good proxy that properly captures this dimension.

We will use three different measures to try and capture investor awareness.

First, analyst coverage (COVERAGE), calculated as the average number of analysts covering the stock over the analyzed window. The idea is that the more analysts cover a stock, the faster the information flow.

A second measure we employ is forecast dispersion (DISPERSION), the standard deviation of yearly analyst forecasts divided by the average forecast.

We expect a decline in dispersion once the stock is added to S&P 500.

The results presented in Table 2 partially confirm our expectations, as the t and z values are not significant.

The third proxy for investor awareness is the Shadow cost, as suggested by Merton (1987). It represents the difference between the returns expected by a fully diversified investor and an "under-diversified" investor. This measure builds upon the idea that an investor only trades in a finite set of securities he/she is aware of and will be subject to under-diversification.

We believe that, once affiliated with the index, a larger number of investors will become aware of the company, leading to lower shadow costs. Lower shadow costs will minimize the premium expected by the under-diversified investor, thus leading to a higher price for the added security.

We compute shadow cost as suggested by Kadlec & McConnell (1994). Excess return is the return of security *i* in excess of the stock market, and MV is the market value.

$$SC_i = \frac{\sigma(ExcessReturn)_i}{S\&P\ 500\ MV} * \frac{MV_i}{Number\ of\ Shareholders} \tag{4}$$

We notice a small significant decrease in shadow cost for our sample, suggesting that more investors become "aware" of the added companies.

Other variables

We use a set of additional control variables:

(1) Exchange dummy – companies listed on NYSE are more familiar to investors (Chen et al. 2004);
(2) ROA[9] – an increase in ROA should lead to higher abnormal returns;
(3) Book to Market Value – an increase in book to market value should represent an investment opportunity (an undervalued stock);
(4) Leverage as Debt to capital and Debt to equity. Investors have less faith in highly indebted companies and will require a higher risk premium to trade them.

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[9] Several studies (i.e., Denis et al. (2003), Chan et al. (2013a)) suggest that affiliation to an index can be a stimuli for company's management, that should improve it's overall performance.

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Results in Table 2 suggest an increase in analyst coverage following the addition event. According to Chan et al. (2013) it is a sign of an improvement in price efficiency as more information will reach the market. However, the difference between the two estimation windows is not statistically significant. We also notice that the increased coverage is accompanied by an increased EPS forecast, suggesting higher optimism levels. Baran & King (2014) explain this optimism through the additional event optimism, while Denis et al. (2003) believe it might result from an improvement in the company's performance. A decline in ROA leads us to believe that Baran & King's (2014) hypothesis regarding optimism is more likely.

There is no significant change in company sizes following the addition event, while the number of shareholders increases by about 50%. We believe that this increase is caused by an increase in institutional holdings[10]. Chan et al. (2003) report a 40% increase in institutional holdings in their sample.

Table 2.
t-stat and Mann-Whitney z-stat for the difference between windows.

	(-260, -31)	(31, 260)		
	mean	mean	t-stat	Mann–Whitney
ILLIQ (x10^4)	0.479	0.211	*-0.78*	*-3.97*
BID-ASK	0.2762	0.3154	*2.02*	*2.13*
TURNOVER	0.0105	0.0157	*0.76*	*2.04*
ZEROS	0.0888	0.0806	*-0.51*	*-1.87*
EPS	1.6638	2.033	*2.47*	*2.5*
COVERAGE	11.8415	12.1336	*0.38*	*0.47*
DISPERSION	0.2503	0.2005	*-1.25*	*-1.37*
SIZE	8.7253	8.9291	*3.43*	*4.41*
ROA	8.1881	7.3482	*-1.12*	*-0.7*
DEBT/EQ	1.2014	0.8404	*-1.08*	*-0.23*
DEBT/CAP	0.2964	0.3368	*1.76*	*3.19*
SHAREHOLDERS	19773	29649	*1.65*	*2.14*
SHADOW COST(10^6)	0.0352	0.0287	*-0.51*	*-2.24*

c. Main results

To see the extent to which (i)liquidity and investor awareness are responsible for abnormal return generation in the case of S&P 500 index affiliation and to capture the dynamics of this relationship, we estimate multiple multivariate regressions on the pre-event and post-event windows.

The purpose is to isolate any changes in return behavior consistent with changes in the informational environment.

[10] Coffee (1991) and Agarwal(2009) provide evidence in support of insitutional ownership impact on stock liquidity.

The dependent variable is abnormal return, while the independent variables are a collection of liquidity and investor awareness proxies accompanied by control variables.

As such, we estimate the following regression:

$$AR_i = LIQ_i + IA_i + \sum_{i=1}^{k} C_{i,k} + \epsilon \qquad (5)$$

where, LIQ is the liquidity proxy, IA is the investor awareness proxy, and C are control variables.

Although all regressions were estimated on abnormal returns using all three abnormal return proxies, we will report only the results for the abnormal return computed from the market model unless new evidence is available.

Pre-event window

Tables 3-5 aggregate results for different (i)liquidity measures' impact on abnormal returns during the pre-event window. ILLIQ & ZEROS are statistically significant, whereas BID-ASK & TURNOVER are not.

Table 3.
Pre-event window (-260, -31) regression results

	-1	-2		-3	-4
ILLIQ	-0.58464**	-0.53537**	ZEROS	-0.006165***	-0.00562***
	(-2.67)	(-2.40)		(-6.02)	(-5.10)
DISPERSION	0.00006	-0.00001	DISPERSION	0.000086	0.00003
	(0.75)	(-0.12)		(1.03)	(0.42)
DUMMY_NASDAQ	0.00042***	0.0003**	DUMMY_NASDAQ	0.000216	0.00014
	(3.02)	(2.16)		(1.57)	(1.02)
BTMV	-0.00008***	-0.00008***	BTMV	-0.000074***	-0.00008***
	(-3.41)	(-4.41)		(-4.65)	(-5.55)
ROA	0.00001*	0.00001	ROA	0.000014**	0.00001***
	(1.88)	(1.54)		(2.1)	(1.81)
DEBT_CAP	-0.00042**	-0.00028	DEBT_CAP	-0.000415**	-0.0003*
	(-2.27)	(-1.58)		(-2.17)	(-1.66)
constant	0.0004***	0.00077***	Constant	0.000947***	0.00124***
	(3.64)	(3.16)		(6.37)	(4.71)
Industry Dummy	NO	YES	*Industry Dummy*	NO	YES
F-stat	4.5	4.69	***F-stat***	11.12	6.65
R-squared	0.0577	0.1224	***R-squared***	0.1466	0.1776

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

These results are consistent with the efficient market hypothesis and confirm the low informational content of stock prices before their addition to S&P 500. Less informed traders will lead to more friction regarding price informativeness (Holden & Subrahmanyam, 1992). Moreover, investors will demand an illiquidity premium for trading illiquid stocks, leading to lower abnormal returns (Amihud & Mendelson, 1980).

Changing the proxy for abnormal returns and controlling for industries does not affect the results.

Table 4.
Pre-event window (-260, -31) regression results (2)

	-1	-2		-3	-4
ILLIQ	-0.54045**	-0.53789**	ZEROS	-0.006439***	-0.00623***
	(-1.96)	(-2.04)		(-6.01)	(-5.43)
COVERAGE	0.00002*	0.00001	DISPERSION	0.000004	-0.00001
	(1.84)	(0.53)		(0.41)	(-0.84)
DUMMY_NASDAQ	0.00052***	0.00038**	DUMMY_NASDAQ	0.000346**	0.00022
	(3.25)	(2.42)		(2.25)	(1.46)
BTMV	-0.00008***	-0.00008***	BTMV	-0.000075***	-0.00009***
	(-3.49)	(-4.83)		(-4.88)	(-6.35)
ROA	0.0000116	9.43E-06	ROA	0.0000115*	9.83E-06
	(1.59)	(1.19)		(1.67)	(1.32)
DEBT_TO_EQ	-0.00001**	-0.00001***	DEBT_CAP	-0.000008**	-0.00001***
	(-2.20)	(-2.96)		(-2.23)	(-2.82)
constant	0.00007	0.00059**	constant	0.000827***	0.00137***
	(0.54)	(2.16)		(4.6)	(4.61)
Industry Dummy	NO	YES	*Industry Dummy*	NO	YES
			F-stat		
F-stat	5.83	4.94	***R-squared***	11.69	7.33
R-squared	0.073	0.12222		0.1422	0.1791

Values in brackets are the t-statistics calculated based on errors corrected firm cluster option.
***, **, and * represent significance at 1%, 5%, and 10%.

The lack of significance for implicit BID-ASK and TURNOVER measures can be explained by the fact that they capture different liquidity characteristics. For example, TURNOVER measures trading activity and does not account for price impact, so we can consider it a measure of liquidity without information production (Chen et al. 2004). As such, the lack of significance for this measure, together with strongly significant ILLIQ and ZEROS, could be a sign that price changes pre-addition are influenced by the information flow and the market's ability to incorporate that information rather than a simple change in trading volumes (Chan et al. 2013)

Table 5.
Pre-event window (-260, -31) regression results (3)

	(1)		(2)
BID-ASK Spread	0.000228	TURNOVER	0.00045
	(1.25)		(0.39)
COVERAGE	0	COVERAGE	0
	(0.79)		(0.81)
DUMMY_NASDAQ	0.00036**	DUMMY_NASDAQ	0.00035**
	(2.25)		(2.21)
BTMV	-0.00008***	BTMV	-0.00008***
	(-4.97)		(-4.72)
ROA	9.52E-06	ROA	9.86E-06
	(1.23)		(1.26)
DEBT_TO_EQ	0.00001***	DEBT_TO_EQ	-0.00001**
	(-3.04)		(-2.97)
constant	0.00048*	constant	0.00053*
	(1.75)		(1.93)

	(1)		(2)
Industry Dummy	YES	*Industry Dummy*	YES
F-stat	4.94	***F-stat***	4.69
R-squared	0.1154	***R-squared***	0.1127

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

Results in Table 6 account for the impact of shadow cost. Shadow cost is not significant pre-addition, although its negative coefficients suggest that it could negatively affect abnormal returns. Including this variable does not change the statistical significance of ILLIQ & Zeros coefficients.

Contrary to our expectations, companies listed on NASDAQ have higher abnormal returns than those traded on NYSE. Blume & Edelen (2004) argue that the different exchange mechanics could explain this phenomenon. The authors show that bilateral agreements frequently employed on NASDAQ can lead to higher return generation.

Table 6.
Pre-event window (-260, -31)

AR from	Market Model		Market & Industry Model		Fama-French 3-Factor Model	
	(1)	(2)	(3)	(4)	(5)	(6)
ILLIQ	-0.159351**		-0.1773**		0.06182	
	(-2.22)		(-2.57)		(0.71)	
ZEROS		-0.0036498**		-0.0032637*		-0.0013659
		(-2.23)		(-2.03)		(-0.82)
SHADOW_COST	-559	-628.63	-320.81	-383.17	-536.51	-562.58
	(-0.81)	(-0.86)	(-0.61)	(-0.69)	(-0.77)	(-0.79)
DUMMY_NASDAQ	0.00042**	0.00035*	0.000325*	0.00026	0.00037*	0.00034
	(2.25)	(1.85)	(1.83)	(1.46)	(1.71)	-1.58
BTMV	-0.00008***	-0.00008***	-0.000072***	-0.00007***	-0.00015***	-0.00015***
	(-6.11)	(-6.72)	(-5.15)	(-5.63)	(-11.44)	(-11.80)
ROA	-0.000013	-9.35E-06	-0.00001	-0.00001	-7.37E-06	-6.00E-06
	(-1.40)	(-1.03)	(-1.13)	(-0.78)	(-0.66)	(-0.53)
DEBT_TO_EQ	-0.000005	0	-0.000005	0	-0.00001	-0.00001
	(-1.49)	(-1.26)	(-1.48)	(-1.26)	(-1.58)	(-1.53)
constant	0.001233***	0.00146***	0.000718**	0.00092***	0.00139***	0.00148
	(4.05)	(4.63)	(2.6)	(3.14)	(3.85)	(3.91)***
Industry Dummy	YES	YES	YES	YES	YES	YES
F-stat	6.35	4.92	6.98	3.63	14.48	13.71
R-squared	0.0831	0.0997	0.0702	0.0853	0.12	0.1217

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

Post-event window

In line with our expectations, the coefficients for (i)liquidity measures are not significant for the post-event window. Interestingly, after their addition to S&P 500, companies with higher leverage register higher abnormal returns. We can explain this by the "market leader" branding that comes together with an S&P 500 affiliation, which is associated with higher trust[11] levels. (Merton, 1987)

[11] For details, please refer to Guiso, Sapienza and Zingales (2008).

Table 7.
Post-event window (31,260)

AR from	Market Model		Market & Industry Model		Fama-French 3-Factor Model	
	(1)	(2)	(3)	(4)	(5)	(6)
ILLIQ	-0.279542		-0.27584		-0.33965	
	(-0.34)		(-0.33)		(-0.36)	
ZEROS		-0.00052		-0.00033		0.00118
		(-0.55)		(-0.37)		(1.15)
COVERAGE	0.00000	0.00	0.00000	0.00000	0.00000	0.00000
	(-0.31)	(-0.35)	(-0.57)	(-0.55)	(-0.40)	(0.04)
DUMMY_NASDAQ	-0.00032**	-0.00034	-0.00022	-0.00024	-0.00032**	-0.00031*
	(-2.00)	(-2.15)	(-1.51)	(-1.63)	(-2.00)	(-1.92)
BTMV	0.00013	0.00013	0.00011	0.00011	-0.00002	-0.00003
	(0.79)	(0.79)	(0.69)	(0.68)	(-0.13)	(-0.16)
ROA	-8.1E-07	-7.72e-07	0.00000	0.00000	0.00	1.09e-08
	(-0.27)	(-0.26)	(-0.41)	(-0.41)	(0.04)	(0.00)
DEBT_TO_EQ	-0.00001	-0.00001*	-0.00001	-0.00001	-0.00001	-0.00001
	(-1.87)	(-1.81)	(-0.85)	(-0.76)	(-1.14)	(-1.04)
constant	0.00006	0.00011	0.00002	0.00005	-0.00012	-0.00029
	(0.21)	(0.04)	(0.09)	(0.20)	(-0.41)	(0.381)
Industry Dummy	YES	YES	YES	YES	YES	YES
F-stat	1.68000	1.70000	0.98000	0.99000	1.18000	1.25000
R-squared	0.04130	0.04060	0.02280	0.02160	0.03250	0.22840

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

Unfortunately, our model is not a good descriptor for abnormal returns post-index addition, suggesting there could be other variables, such as stock price co-movement or company-specific risk, that might better describe abnormal return creation post-index addition (Chan et al. 2013b) One other explanation would lay with full price reversal after the addition event, suggesting no significant abnormal return generation after stocks affiliation to the index.

The positive statistically significant coefficient for debt to capital is a sign that investors are more familiar with the companies they believe to be sector leaders (Merton, 1987) and are more likely to entrust their money despite higher leverage ratios, albeit requiring a risk premium to do so.

Table 8.
Post-event window (31,260)

AR from	Market Model		Market & Industry Model		Fama-French 3-Factor Model	
	(1)	(2)	(3)	(4)	(5)	(6)
BID-ASK Spread	0.000269		0.000256		0.000516	
	(1.33)		(1.39)		(1.55)	
TURNOVER		-0.00028		-0.00023		-0.00029*
		(-1.91)		(-1.47)		(-1.69)
COVERAGE	0.00000	0.00	0.00	0.00	0.00	0.00
	(-0.11)	(-0.25)	(-0.34)	(-0.48)	(-0.14)	(-0.32)
DUMMY_NASDAQ	-0.00034**	-0.00033**	-0.000244*	-0.00023	-0.00032**	-0.00033**
	(-2.19)	(-2.08)	(-1.70)	(-1.59)	(-2.00)	(-2.08)
BTMV	0.00012	0.00013	0.000091	0.00011	0.00000	-0.00002
	(0.70)	(0.80)	(0.59)	(0.69)	(-0.06)	(-0.13)

	(1)	(2)	(3)	(4)	(5)	(6)
ROA	-8.61e-07	-8.51e-07	-0.000001	0.00000	-2.78e-07	9.49e-08
	(-0.30)	(-0.29)	(-0.46)	(-0.44)	(-0.09)	(0.03)
DEBT_TO_EQ	-0.00001	-0.00001	-0.000002	-0.00001	-0.00001	-0.00001
	(-1.30)	(-1.88)	(-0.27)	(-0.86)	(-0.98)	(-1.14)
constanta	-0.00004	0.00005	-0.000076	0.00001	-0.00042	-0.00013
	(-0.15)	(0.19)	(-0.34)	(0.07)	(-1.40)	(-0.42)
Industry Dummy	YES	YES	YES	YES	YES	YES
F-stat	1.85000	1.70000	1.10000	1.03000	1.47000	1.27000
R-squared	0.04400	0.04110	0.02570	0.02220	0.03780	0.03190

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

Upon including shadow cost in our regression, we notice it has a strong statistically significant impact on abnormal returns. Moreover, coefficients for ILLIQ, BID-ASK, and TURNOVER in models that include SHADOW COST appear significant at a 10% confidence level.

We follow up and re-run these models over the more isolated estimation window (+101, +260). All above-mentioned variables lose their statistical significance.

As such, the results presented in Table 9.A confirm it is best to use two sets of estimation windows to allow more time for the reconstruction changes to take effect.

Table 9.A.
Post event estimation window (31, 260)

	(1)	(2)	(3)	(4)
ILLIQ	7.31653***			
	(37.81)			
ZEROS		-0.00081		
		(-0.46)		
BID-ASK			0.00052*	
			(1.83)	
TURNOVER				-0.00022 *
				(-1.67)
SHADOW_COST	549.985**	533.817**	588.100**	544.384**
	(2.60)	(2.44)	(2.73)	(2.53)
DUMMY_NASDAQ	-0.00017	-0.00023	-0.00022	-0.00021
	(-0.92)	(-1.24)	(-1.22)	(-1.14)
BTMV	0.00015	0.00010	0.00006	0.00010
	(0.72)	(0.47)	(0.31)	(0.50)
ROA	0.00000	0.00000	0.00000	0.00000
	(-0.93)	(-0.36)	(-0.48)	(-0.42)
DEBT_TO_CAP	0.00008**	0.00009**	0.00009**	0.00008**
	(2.25)	(2.65)	(2.82)	(2.50)
constant	-0.00025	-0.00018	-0.00033	-0.00023
	(-0.65)	(-0.44)	(-0.87)	(-0.60)
Industry Dummy	YES	YES	YES	YES
F-stat	235.88000	1.93000	2.45000	1.98000
R-squared	0.10330	0.02920	0.04040	0.02920

Table 9.B.
Post event estimation window (101, 260)

	(1)	(2)	(3)	(4)
ILLIQ	2.45179			
	(0.30)			
ZEROS		0.00086		
		(0.64)		
BID-ASK			0.00049	
			(1.44)	
TURNOVER				-0.00050
				(-1.55)
SHADOW_COST	200.236	162.146	113.841	198.731
	(1.21)	(1.03)	(0.62)	(1.20)
DUMMY_NASDAQ	0.00026	0.00026	0.00026	0.00025
	(1.21)	(1.25)	(1.22)	(1.19)
BTMV	0.00015	0.00017	0.00012	0.00016
	(0.38)	(0.42)	(0.31)	(0.41)
ROA	0.00001	0.00001	0.00001	0.00001
	(0.75)	(0.72)	(0.58)	(0.76)
DEBT_TO_CAP	0.00005	0.00003	0.00007	0.00004
	(0.14)	(-0.91)	(0.20)	(0.11)
constant	-0.00045	-0.00050	-0.00063	-0.00044
				(-0.82)
Industry Dummy	YES	YES	YES	YES
F-stat	0.90000	0.91000	1.15000	1.06000
R-squared	0.01310	0.01400	0.02110	0.01490

Values in brackets are the t-statistics calculated based on errors corrected by the cluter option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

d. *The difference in difference analysis*

We conclude our study by performing a difference in difference analysis for the event window, similar to Chen et al. (2004), Liu (2011) and Chan et al. (2013a). We consider that the event window[12] starts 30 days prior to the event and lasts through 30 days after. We use this event window to capture any speculative behaviors that might happen weeks before S&P Committee's announcement.

Unlike Chan et al. (2013a), who only use ILLIQ for their difference in difference study, we compute differences for all our variables, as each (i)liquidity measure captures a different side of stock liquidity.

Our dependent variable is the mean abnormal return over the event window, and the regression we estimate is as follows:

$$AR_i = \Delta LICH_i + \Delta IA_i + \sum_{i=1}^{k} \Delta C_{i,k} + \epsilon \tag{6}$$

We notice that abnormal returns during the event window can be explained through ΔTURNOVER, a proxy for changes in trading activity. As expected, companies with higher trading volumes register higher abnormal returns during the event window. This is a stock market anomaly, and it is in line with the price pressure hypothesis (Kim & Kim, 2023; Amihud et al., 2015). Indexers want to buy stocks to re-adjust their portfolios to replicate the new index structure as close to the event date as possible to minimize their tracking error. The price they are willing to pay for the shares is just below the cost they would have to pay for an earlier adjustment. Nevertheless, the information regarding a future index restructuring is already public, causing price pressure from arbitragers willing to profit from indexers' rebalancing.

None of the investor awareness proxies are significant during the event window, although the coefficient sign for shadow cost is positive. It could imply that companies less known to investors will profit more from their affiliation with S&P 500.

As such, we can conclude that companies that were less traded before the event will benefit more from the addition to S&P 500.

Table 10.
Event window (-30, +30)

	(1)	(2)	(3)	(4)
ΔILLIQ	0.00891 (0.25)			
ΔZEROS		-0.00080 (-0.17)		
ΔBID-ASK			0.00003 (0.07)	
ΔTURNOVER				0.00029* (1.65)
ΔSHADOW_COST	175.210 (0.14)	192.867 (0.15)	155.206 (0.12)	172.362 (0.13)

[12] We use a second event window (-15, +65) as a robustness test, which does not affect our findings.

	(1)	(2)	(3)	(4)
DUMMY_NASDAQ	-0.00004	-0.00004	-0.00004	-0.00004
	(-0.09)	(-0.09)	(-0.10)	(-0.09)
ΔBTMV	-0.00010	-0.00010	-0.00010	-0.00010
	(-1.29)	(-1.30)	(-1.28)	(-1.29)
ΔROA	0.00000	0.00000	0.00000	0.00000
	(0.06)	(0.07)	(0.06)	(0.07)
ΔDEBT_TO_CAP	-0.00059	-0.00060	-0.00059	-0.00059
	(-0.69)	(-0.71)	(-0.69)	(-0.69)
constanta	0.00045	0.00045	0.00044	0.00045
	(0.51)	(0.50)	(0.51)	(0.51)
Industry Dummy	YES	YES	YES	YES
F-stat	0.79000	0.73000	0.75000	1.47000
R-squared	0.02790	0.02800	0.02790	0.02810

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.

5. Conclusions

We examine the dynamics of abnormal return determinants around the event of S&P 500 reconstruction on a sample of 522 additions. Our results suggest that affiliation with S&P 500 can affect a stock's abnormal return determinants.

First, over the pre-event window, where there is less information available about the companies analyzed, abnormal returns are explained through the liquidity hypothesis, consistent with the efficient market hypothesis (Fama, 1970). As such, investors will require higher illiquidity premia for trading less-liquid stocks.

During the event window, abnormal returns are explained through the price pressure hypothesis, as higher demand from institutional investors and arbitragers leads to higher prices and abnormal returns. Increased trading activity positively affects the returns of newly added companies.

The post-event window is characterized by the least informational content. Neither liquidity, investor awareness, nor fundamental factors appear to be responsible for abnormal returns during that window. This phenomenon can be explained through full price reversal over the longer time-frame, suggesting no significant abnormal returns being generated after inclusion in the S&P 500 Index.

Our results are consistent with existing literature. Additionally, we show that during the event window, price impact, as measured by illiquidity, and trading costs, as captured by the implicit bid-ask spread, do not influence the abnormal return creation, while increased demand for newly added stocks does.

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Appendix 1

A. Additions				Industry						
Year	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financial	IT Services	Utilities	Real Estate
1994	12	15	42	35	19	14	18	18	14	2
1995	0	0	0	2	0	2	6	2	1	0
1996	0	0	3	1	1	1	4	0	0	0
1997	1	0	2	1	1	1	6	3	2	0
1998	0	0	3	3	1	1	5	0	4	0
1999	2	1	2	4	1	0	2	4	2	0
2000	3	0	1	2	0	1	1	4	1	0
2001	0	0	2	0	1	0	1	3	0	1
2002	0	0	3	2	0	1	3	1	0	1
2003	0	0	0	1	1	1	0	0	1	2
2004	1	0	0	1	0	2	1	0	0	0
2005	2	0	0	4	2	1	1	0	0	2
2006	1	0	2	1	0	0	1	5	0	3
2007	1	0	4	5	1	0	3	2	0	4
2008	3	2	2	1	1	3	1	2	3	0
2009	1	2	3	4	1	0	0	4	1	3
2010	2	0	1	3	0	0	2	1	1	0
2011	0	1	1	3	0	2	1	1	0	1
2012	1	1	1	3	1	0	0	2	0	1
2013	1	0	2	4	0	2	0	0	0	1
2014	0	0	2	3	0	1	1	1	0	1
2015	0	0	3	7	1	3	0	2	0	3
2016	0	1	4	5	0	3	2	1	2	5
2017	0	0	2	3	0	5	3	7	0	3
2018	1	1	4	3	1	1	2	3	1	0
2019	0	0	0	0	0	1	1	0	0	0
TOTAL	32	24	89	101	33	46	65	65	34	33

The final sample of additions for 1994-2019. Breakdown by industry is done based on the GICS classification. To be included in the final sample, companies must have at least 2 years of continuos returns around the event day.

Appendix 2

B. Deletions	Industry									
Year	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financial	IT Services	Utilities	Real Estate
1994	0	0	0	0	0	0	0	0	0	0
1995	0	0	1	2	0	0	1	0	0	0
1996	0	0	1	2	0	0	0	0	0	0
1997	0	0	0	0	0	1	1	0	0	0
1998	0	0	2	0	0	0	2	0	0	0
1999	1	1	4	2	0	0	0	0	0	0
2000	1	0	2	1	1	0	0	0	0	1
2001	1	1	0	0	0	0	0	0	0	1
2002	0	2	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0	0	1	0
2004	0	1	1	1	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	1	0	0
2006	0	0	1	1	0	0	0	0	0	0
2007	0	0	1	0	0	0	0	3	0	0
2008	1	1	3	3	1	0	3	2	1	0
2009	0	0	2	1	0	0	1	2	0	1
2010	0	0	0	2	0	0	1	0	0	0
2011	0	0	1	0	0	0	0	0	0	1
2012	1	0	0	1	0	0	0	0	0	0
2013	0	0	0	2	0	0	1	5	0	0
2014	0	2	0	1	0	0	1	1	0	0
2015	1	0	1	0	0	0	1	1	0	0
2016	1	0	2	2	1	1	1	0	0	0
2017	4	0	2	4	0	0	0	1	0	0
2018	2	0	1	1	1	1	1	0	1	0
2019	0	0	0	0	0	0	0	0	1	0
TOTAL	13	9	25	26	4	3	14	16	4	4

The final sample of deletions for 1994-2019. Breakdown by industry is done based on the GICS classification. To be included in the final sample, companies must have at least 2 years of continuous returns around the event day.

Appendix 3. Regression results for the event window

Event window (-30, +30). AR as computed from the market model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔILLIQ	-0.22928	-0.24022						
	(-0.52)	(-0.41)						
ΔZEROS			-0.0009	-0.0006				
			(-0.27)	(-0.18)				
ΔBID-ASK					-0.0003	-0.0003		
					(-0.86)	(-0.89)		
ΔTURNOVER							0.0004 ***	0.0005 **
							(3.80)	(2.37)
ΔDISPERSION	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003*	0.0003	0.0003*
	(1.48)	(1.63)	(1.48)	(1.63)	(1.53)	(1.71)	(1.49)	(1.66)
DUMMY_NASDAQ	0.0003	0.0002	0.0003	0.0002	0.0003	0.0002	0.0003	0.0002
	(0.83)	(0.60)	(0.84)	(0.60)	(0.83)	(0.61)	(0.85)	(0.60)
ΔBTMV	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-1.60)	(-1.38)	(-1.60)	(-1.37)	(-1.62)	(-1.40)	(-1.60)	(-1.37)
ΔROA(10^4)	-0.1100**	-0.1040**	-0.1090**	-0.1030**	-0.1100**	-0.1030**	-0.1100**	-0.1030**
	(-2.47)	(-2.15)	(-2.44)	(-2.13)	(-2.34)	(-2.03)	(-2.44)	(-2.13)
ΔDEBT_CAP	0.0006	0.0007	0.0006	0.0007	0.0006	0.0006	0.0007	0.0007
	(1.37)	(1.31)	(1.36)	(1.30)	(1.29)	(1.230	(1.38)	(1.34)
constanta	-0.0002	-0.0003	-0.0002	-0.0003	-0.0002	-0.0003	-0.0002	-0.0003
	(-0.75)	(-0.58)	(-0.75)	(-0.58)	(-0.65)	(-0.44)	(-0.77)	
Industry Dummy	NO	YES	NO	YES	NO	YES	NO	YES
F-stat	2.15000	1.71000	2.13000	1.70000	2.07000	1.70000	5.33000	3.27000
R-squared	0.01790	0.03730	0.01800	0.03730	0.01970	0.03930	0.0181	0.0376

Values in brackets are the t-statistics calculated based on errors corrected by the cluster option for companies. ***, **, and * represent significance at 1%, 5%, and 10%.