SHORT-SELLING AND THE DISAPPEARING INDEX EFFECT IN EUROPEAN BLUE-CHIP INDEXES

Evidence from the EURO STOXX 50 and the FTSE 100

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Short-Selling and the Disappearing Index Effect in European Blue-Chip Indexes: Evidence from the EURO STOXX 50 and the FTSE 100, 2012–2026

Abstract:

This paper studies whether short-selling activity attenuates the abnormal returns associated with stock additions to and deletions from major European equity indexes. Using a hand-collected sample of 304 reconstitution events for the EURO STOXX 50 and the FTSE 100 between November 2012 and April 2026, we utilize the European Union Short Selling Regulation, which since 2012 has required holders of net short positions exceeding 0.5% of share capital to disclose them publicly (European Parliament and Council, 2012). Pooling tests (Welch's t on means, $p = 0.51–0.67$; Chow F-tests on regression coefficients, $p = 0.20–0.71$) confirm that the two samples can be combined for the headline analysis. We find that the canonical index-inclusion effect documented for the U.S. by Shleifer (1986) and recently shown to have disappeared by Greenwood and Sammon (2025) is also absent in our European sample on average: announcement-window cumulative abnormal returns are statistically indistinguishable from zero in both directions. The effect that remains is concentrated on the deletion side of the EURO STOXX 50 in 2013–2017 ($CAR = -7.7\%$, $t = -2.0$). Splitting the cross-section before and after 2018, we find that disclosed short interest is negatively associated with deletion CARs in the early period ($\beta = -2.31$, $t = -1.92$, $p = 0.06$) but the effect attenuates in the late period ($\beta = -0.07$, n.s.) mirroring the disappearance of the index effect itself. Our results extend the Greenwood-Sammon finding to European blue-chip indexes and provide the first direct evidence on the role of short-selling activity around index reconstitutions, cushioning additions and compounding deletions.

Keywords:

Index Effect, Short Selling, EURO STOXX 50, FTSE 100, Limits to Arbitrage

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1. Introduction

Suppose you own shares in a mid-sized British company that has been steadily growing for years. On a Wednesday afternoon, the FTSE 100 committee announces that the company will join the index in three weeks because its market value has risen above the threshold for inclusion. By the next morning, before any new information about the company has surfaced, its share price is up several percent. Why? The answer has nothing to do with what the company sells, who its customers are, or what it earned last quarter. It has to do with the billions of euros and pounds parked in passive index funds, which by mandate hold every FTSE 100 stock in proportion to its weight. Once the company joins the index, those funds must buy, and the resulting wave of mechanical buying pushes the price up even though nothing about the underlying business has changed.

This phenomenon, stocks added to a major equity index rising in price, and stocks removed from one falling, simply because of mechanical buying or selling by index funds, is known as the index-inclusion effect, and it has occupied finance researchers for nearly forty years. Shleifer (1986) was the first to document it: stocks newly added to the S&P 500 earned an abnormal return of roughly 2.8% on the announcement day, and the gain persisted for at least ten to twenty trading days afterwards. Because S&P's selection criteria draw on publicly available information and are not designed to identify future winners, the price reaction cannot be explained by news about firm fundamentals. It is a price reaction to demand alone, and it sits awkwardly with the textbook view that the abundance of close substitutes among stocks should leave demand curves for individual securities almost flat.

In a recent and influential paper, Greenwood and Sammon (2025) turn this textbook puzzle on its head: the average abnormal return associated with S&P 500 additions has fallen from 7.4% in the 1990s to less than 1% over the past decade, even as the share of total market value held in index funds has continued to climb. They attribute the decline to a combination of forces operating in parallel, the rise of paired migrations between related indexes, the increased predictability of index changes, and a substantial improvement in the market's capacity to provide liquidity around rebalancing dates. Their most striking finding is that, even though passive funds today buy roughly seven percent of an added stock's shares outstanding (Greenwood and Sammon, 2025), the total institutional ownership of that stock barely moves. Some other set of institutions is quietly stepping in to sell shares to the index funds, absorbing the demand shock. The puzzle is no longer the existence of the index effect but its disappearance, and the open question is who, exactly, now stands on the other side of the passive trade. Aghaee (2022) offers complementary evidence that this 'flattening of demand curves' runs through changes in measured arbitrage risk, but he does not observe the arbitrageurs themselves.

This thesis takes up that open question for European blue-chip indexes, asking specifically: do short sellers, a class of arbitrageurs whose positions, unlike most others, can be observed directly, provide some of the liquidity that has caused the index effect to shrink in European blue-chip indexes? The economic logic is simple. When a stock is announced as a forthcoming deletion, short sellers can open or maintain positions during the [AD, ED] window, adding supply alongside the forced selling by index funds and amplifying the downward price pressure. On the addition side, the more short-selling activity around the event window, the smaller the positive abnormal return ought to be. On the deletion side, short sellers adding supply alongside mechanical index-fund selling should compound the negative abnormal return, making it larger in absolute value. We test both predictions directly using publicly disclosed short positions. To answer this question, we hand-collect every reconstitution event for the EURO STOXX 50 and the FTSE 100 between November 2012, the introduction of the EU Short Selling Regulation, which requires public disclosure of net short positions above 0.5% of issued share capital, and April 2026. After applying the contamination filters used by Greenwood and Sammon (2025), we end up with 304 events: 58 EURO STOXX 50 events (31 additions, 27 deletions) and 246 FTSE 100 events (126 additions, 120 deletions).

For each event we compute cumulative abnormal returns over three windows and aggregate disclosed short positions to the firm-event level into a measure we label SSA. We test whether the index effect can be pooled across the two indexes. Pooling is supported: a Chow test on the cross-sectional regression yields p-values between 0.20 and 0.71. We then run pooled regressions of CAR on SSA with an index fixed effect and the standard Greenwood-Sammon controls.

Three results stand out. First, averaged across the 304-event pooled sample, the announcement-window CAR is statistically indistinguishable from zero, both for additions (mean = +0.16%, t = 0.61) and for deletions (mean = -0.25%, t = -0.67). The Greenwood-Sammon disappearance applies to European blue-chip indexes just as it does to the S&P 500. Second, what residual effect remains is concentrated on the deletion side of the EURO STOXX 50 in the earliest sub-period (2013–2017 mean total CAR = -7.7%, t = -2.0). The FTSE 100, fully rule-based and almost perfectly anticipated, shows no detectable effect in any window. Third, when we split the cross-sectional regression of deletion CAR on SSA before and after 2018, the SSA coefficient is negative in the early period (β = -2.31, t = -1.92, p = 0.06) and indistinguishable from zero in the late period (β = -0.07). Disclosed short interest, in other words, was associated with larger deletion-side price drops in precisely the years when the deletion effect was substantial, and that association faded along with the effect itself.

The remainder of the paper proceeds as follows. Section 2 surveys the relevant literature. Section 3 describes the data, defines our variables, and lays out the empirical methodology. Section 4 presents the results. Section 5 discusses implications and concludes.

2. Literature Review

2.1 The index-inclusion effect

Shleifer (1986) and Harris and Gurel (1986) opened this literature by documenting that stocks added to the S&P 500 earn statistically significant positive abnormal returns at the announcement of inclusion, on the order of 2.8% on announcement day in Shleifer's sample, and that those returns persist for ten to twenty trading days afterwards. The setting is unusually clean: S&P's selection criteria are publicly available and are explicitly unrelated to future firm performance, which makes the inclusion event one of the rare cases in which the announcement is essentially mechanical and the price reaction cannot easily be attributed to news about fundamentals. Together these two papers established the index-inclusion effect as the canonical example of non-fundamental price pressure.

Shleifer read his findings as evidence that demand curves for individual stocks slope downward, that, contrary to the textbook view in which the availability of close substitutes should make demand for any given stock nearly perfectly elastic, an outward shift in demand from index funds materially moves the price. The literature subsequently sharpened this view from several angles. Lynch and Mendenhall (1997) showed that announcement-day returns are followed by partial reversals around the effective date, consistent with temporary price pressure that decays once the mechanical rebalancing is complete. Wurgler and Zhuravskaya (2002) shifted attention to the cross-section, showing that the inclusion effect is systematically larger for stocks with fewer close substitutes, and reframed the underlying question: demand curves slope down not because the law of one price fails outright but because arbitrageurs face genuine risk when they try to hedge an overpriced added stock with imperfect substitutes.

2.2 The disappearing index effect

Greenwood and Sammon (2025) deliver the most striking recent contribution to this literature. They show that the average abnormal return associated with S&P 500 additions rose from about 3.4% in the 1980s to 7.4% in the 1990s, then declined to 5.2% in the 2000s and to less than 1.0% over the past decade, statistically indistinguishable from zero. Deletions follow a symmetric pattern. All of this happened despite the share of total market capitalization held in S&P 500-tracking funds rising from near zero to roughly seven percent, which implies that the price-impact multiplier on a given demand shock has fallen by a factor of about twenty. They credit several forces working in tandem: an increase in paired migrations from the S&P MidCap 400 that mechanically shrink the net demand shock; the growing predictability of index changes, which makes anticipatory front-running easier; and a broad rise in the market's overall capacity to provide liquidity around index events. Their most telling finding is that, although passive trackers buy seven to eight percent of an added stock's shares, total institutional ownership of that stock hardly moves. Other institutions are stepping in to absorb the demand shock, and the open question is who they are.

2.3 Arbitrage risk as the channel

Aghaee (2022) offers complementary evidence on the mechanism behind the flattening. He observes that when a stock enters or leaves the S&P 500, the index divisor adjusts to preserve continuity, and this adjustment mechanically shifts the portfolio weight of every stock that remains in the index. The weight changes are economically tiny, but they generate a clean, information-free demand shock on incumbent stocks. Estimating the price reaction to these tiny mechanical shocks, Aghaee finds a price-impact multiplier of roughly 1.5 in the early 2000s falling toward zero in the late 2010s, mirroring the decline in the index effect itself but isolated from any informational confound. Building on Wurgler and Zhuravskaya (2002), he then shows that arbitrage risk is the channel between demand and prices: once the interaction of arbitrage risk and the demand shock is included as a regressor, the direct demand coefficient is no longer significant. Aghaee identifies the channel but does not observe the arbitrageurs flowing through it. This thesis takes up one specific class of arbitrageurs, short sellers, whose positions can be measured directly.

2.4 Short-sale constraints

The literature on limits to arbitrage gives the framework for our hypothesis. Shleifer and Vishny (1997) argued that arbitrage in real markets is risky, capital-constrained, and delegated. Within that framework, short-sale constraints introduce a fundamental asymmetry: an underpriced stock can always be bought, but selling short an overpriced one may be prohibitively expensive or institutionally impossible. Miller (1977) showed that when investors disagree and short selling is constrained, market prices reflect only the most optimistic views. Nagel (2005) advanced this logic empirically, showing that cross-sectional return anomalies are dramatically stronger among stocks with low institutional ownership, his proxy for binding short-sale constraints, and that the variation is driven entirely by the short side. The implication for our setting is that the index-inclusion effect should be smaller when short-sale constraints are less binding, a prediction that has not previously been tested with directly observed short-selling positions.

A smaller body of work has looked at the inclusion effect outside the United States. Deininger, Kaserer and Roos (2000) document significant positive abnormal returns around DAX 30 additions that did not fully reverse. Vespro (2006) finds temporary price effects around CAC 40 and AEX reconstitutions that largely reverse within weeks. Chakrabarti, Huang, Jayaraman and Lee (2005) conclude that the effect is generally weaker outside the U.S. and attribute the difference to the smaller passive investment sector elsewhere. Mazouz and Saadouni (2007) report sizeable price and volume effects around FTSE 100 reconstitutions, with notable asymmetry between additions and deletions. None of these studies investigates the mechanisms through which markets absorb the shock, and none exploits a regulatory regime that allows direct observation of short-selling activity.

The EU Short selling, requiring public disclosure of net short positions above 0.5% of issued share capital, provides a dataset in which the arbitrageurs Greenwood and Sammon leave unidentified, can be directly observed.

2.5 Contribution

Each of the papers most closely related to ours captures a piece of the mechanism. Greenwood and Sammon establish that liquidity provision around index events has improved over time. Aghaee identifies arbitrage risk as the channel. Nagel shows that short-sale constraints govern who is in a position to provide such liquidity. Our thesis sits at the intersection of these three.

Our contribution is fourfold. First, we provide the first direct evidence on the role disclosed short selling plays around index reconstitutions, cushioning of mechanical buying on the addition side and compounding of mechanical selling on the deletion side. This fills in part of what Greenwood and Sammon (2025) leave open about the identity of the marginal liquidity providers. Second, we give the arbitrage-risk channel of Wurgler and Zhuravskaya (2002) and Aghaee (2022) a partial test of the arbitrage-risk channel using observable arbitrageur positions. Third, by exploiting the EU SSR’s mandatory disclosure regime, we move beyond the indirect proxies that earlier studies have had to rely on. Fourth, we extend the European literature past mere price-effect documentation toward an explicit mechanism test, showing along the way that the disappearance of the index effect is a feature of European blue-chip indexes as well, not a U.S.-specific story.

3. Data and Methodology

3.1 Data

The sample consists of reconstitution events for the EURO STOXX 50 and FTSE 100 from November 2012, when the European Union Short Selling Regulation was implemented, to April 2026. The EURO STOXX 50 includes the fifty largest publicly listed companies in the eurozone and is reconstituted annually in September. Its index committee applies a ranked screen based on free-float market capitalization, with some discretion over the cutoff (Qontigo, 2025). The FTSE 100 consists of the hundred largest UK-listed companies and is reconstituted quarterly (March, June, September, December) based on a fully rule-based ranking of free-float market capitalization (FTSE Russell, 2025). Collectively, these two indexes encompass nearly all the largest publicly traded companies in their respective geographies. Together, they can serve as the European counterpart to the U.S. S&P 500, as Greenwood and Sammon (2025) examined.

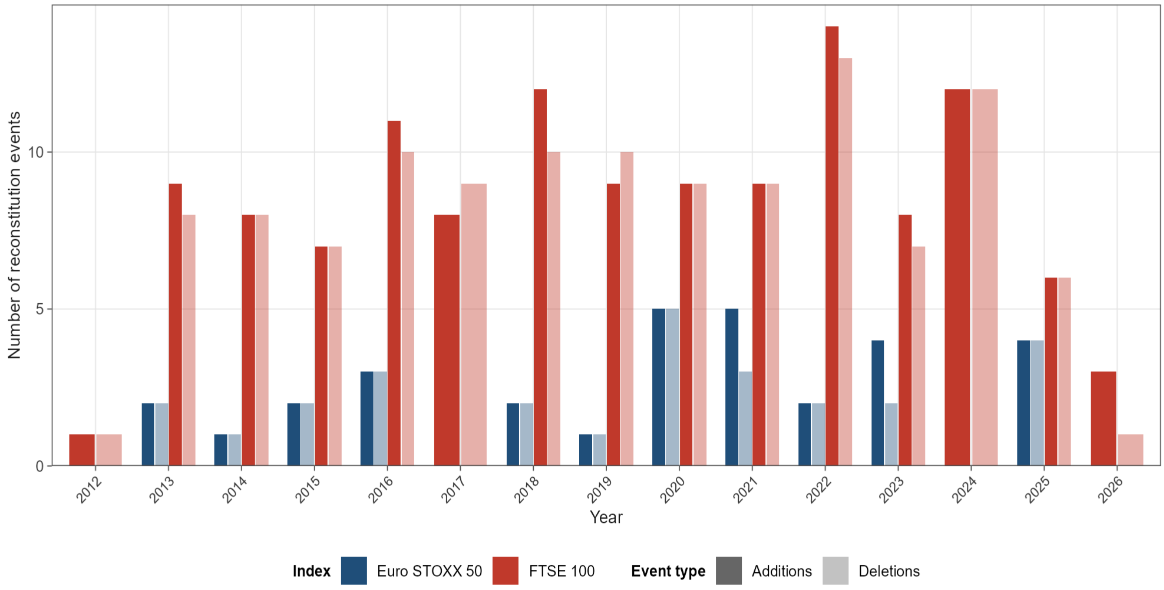
Index events are sourced from STOXX and FTSE Russell press releases and cross-verified with Bloomberg, Refinitiv, Reuters, and S&P Capital IQ for announcement and effective dates. Consistent with Greenwood and Sammon (2025), two contamination filters are applied. First, events involving corporate actions, specifically major mergers and acquisitions financed by stock-for-stock compensation, are excluded to avoid confounding firm-specific news with index-change shocks. Second, stocks newly listed or delisted within 30 days of the announcement or effective date are excluded to ensure adequate time for price discovery. Additionally, two events are removed due to insufficient data. The final sample consists of 304 events: 58 EURO STOXX 50 events (31 additions, 27 deletions) and 246 FTSE 100 events (126 additions, 120 deletions). Table 1 presents the year-by-year composition of the sample.

Table 1. *Sample composition by year, index, and event type. Each cell reports the number of events in that combination after application of contamination filters.*

Year	STOXX Add	STOXX Del	FTSE Add	FTSE Del	Total
2012	0	0	1	1	2
2013	2	2	9	8	21
2014	1	1	8	8	18
2015	2	2	7	7	18
2016	3	3	11	10	27
2017	0	0	8	9	17
2018	2	2	12	10	26
2019	1	1	9	10	21
2020	5	5	9	9	28
2021	5	3	9	9	26
2022	2	2	14	13	31
2023	4	2	8	7	21
2024	0	0	12	12	24
2025	4	4	6	6	20
2026	0	0	3	1	4
Total	**31**	**27**	**126**	**120**	**304**

Figure 1 shows the sample is balanced across additions and deletions and across early and late sub-periods. The eight STOXX deletions in 2013–2017 drive much of the early-period heterogeneity.

Figure 1. Sample composition by year, index, and event type.



Solid bars: additions. Faded bars: deletions.

Daily share returns and trading volumes are computed from dividend-adjusted closing prices drawn from S&P Capital IQ and cross-checked against Refinitiv Workspace. Daily benchmark returns are computed from the closing values of the EURO STOXX 50 and the FTSE 100 indexes, also from S&P Capital IQ. Float-adjusted shares outstanding and the number of analysts following each firm are likewise from S&P Capital IQ.

Short-selling data are derived from public registers maintained under Article 6 of the EU Short Selling Regulation. Since November 2012, holders of net short positions exceeding 0.5% of issued share capital are required to publicly disclose those positions, while positions under this threshold remain unobservable. The unit of observation in the public register is a holder-firm-day. For each event in the sample, all disclosures for the corresponding firm are collected during the window between the announcement date (AD) and the effective date (ED). The selection of the [AD, ED] window, rather than a symmetric event window, is based on the rationale that AD marks the point at which forced demand becomes public knowledge, and ED is when it is resolved. Short-selling activity (SSA) captures positioning within the exact interval when arbitrageurs are incentivized to act. This approach follows Mazouz and Saadouni (2007), who apply a similar announcement-to-effective window in their study of the FTSE 100. From the firm-day series, two summary measures are constructed: SSA_{max}, the maximum daily disclosed short interest within [AD, ED], and SSA_{mean}, the mean value over the time window. The primary specifications utilize SSA. Due to the 0.5% threshold, SSA is left-censored, and events with no holder above the threshold are coded as SSA = 0, representing the lower tail of the disclosure distribution.

Of the 304 events in the pooled sample, 118 (39%) have at least one disclosed short position during the [AD, ED] window: 21 of 58 STOXX events (36%) and 97 of 246 FTSE events (39%). The disclosure rates are nearly identical across indexes, reflecting consistent regulations and enforcement that mitigate concerns about differences in regulatory regimes.

Following Brexit, the United Kingdom's FCA maintained the 0.5% disclosure threshold inherited from the EU SSR (Financial Conduct Authority, 2021), ensuring direct comparability of data between the two indexes throughout the sample period.

Figure 2 shows that passive AUM tracking the FTSE 100 grown rapidly since 2014, while STOXX 50 tracker AUM grew more slowly. Under the Greenwood-Sammon mechanism, larger passive AUM should produce larger mechanical demand shocks, all else equal. However, the AUM consist of the 4-6 largest ETFs tracking the index.

Figure 2. Total AUM of passive ETFs tracking each index (local currency billions).

GBP for FTSE 100; EUR for Euro STOXX 50.

3.2 Variable construction

Cumulative abnormal returns (CARs) are computed for each event over three windows. Following Greenwood and Sammon (2025), the daily abnormal return is

$$AR_{i,t} = R_{i,t} - R_{mt} \qquad (1)$$

where $R_{i,t}$ is the daily return on stock i and $R_{m,t}$ is the daily return on the relevant benchmark index

(the EURO STOXX 50 for STOXX events and the FTSE 100 for FTSE events). A market-adjusted model is used rather than a market-model method with estimated α and β for two reasons. First, this approach aligns exactly with Greenwood and Sammon (2025), maintaining comparability with their S&P 500 results. Second, in a sample of this size, the noise introduced by fitting a separate beta for each event would compound rapidly across events.

Cumulative abnormal returns over a window [to, t1] are then

$$CAR_i[t_0, t_1] = \Sigma_{t=t_0}{}^{t_1} AR_{i,t} \qquad (2)$$

summed over the trading days in the window. Three windows are reported: an announcement window [AD-1, AD+1], an effective window [ED-1, ED+1], and a total window [AD-1, ED+1], which captures the full price impact of the index change. Additionally, two pre-event windows, [AD-50, AD-1] and [AD-20, AD-1], are reported to test for front-running drift, consistent with the approach in Greenwood and Sammon's Table IV.

The control variables follow the specification in Greenwood and Sammon (2025), with adjustments for the European context. Size is defined as float-adjusted market capitalization at AD-1, reflecting the use of free-float adjustment in both STOXX and FTSE index methodologies, in contrast to Greenwood and Sammon's outstanding-shares measure. Size is the market cap of the individual company relative to the market cap of all constients of the index at the same time. Turn is the average daily turnover (volume divided by float shares) over [AD-250, AD-1]. WZ denotes the Wurgler–Zhuravskaya arbitrage-risk measure (Wurgler and Zhuravskaya, 2002), estimated as the residual variance from a regression of the firm's daily returns on the index's daily returns over [AD-250, AD-1], corresponding to Aghaee's (2022) A1 measure. Cover represents the number of sell-side analysts covering the stock at the most recent earnings announcement prior to AD.

Table 2 shows that deletions carry roughly three times the disclosed short interest of additions (mean SSA_max = 0.84% vs. 0.28%), consistent with the asymmetry predicted by Nagel (2005) and Miller (1977). Summary statistics for the sample are presented in Table 2.

Table 2. *Summary statistics of the pooled sample (N = 304 events). CARs are in percent. SSA is expressed as a percentage of issued share capital. Size is expressed as a % of total market cap of the index. Turn is the daily turnover. WZ is the residual variance from the AR(1) market-model regression × 104. Cover is the number of analysts.*

Table 2 (Panel A). Summary statistics, Additions (N=157). CARs in %. SSA in % of share capital.

variable	N	Mean	SD	P25	Median	P75	Min	Max
CAR_ann	153	0.162	3.313	-1.357	0.037	1.760	-16.924	12.575
CAR_eff	153	0.314	3.627	-1.217	0.135	1.481	-13.267	20.532
CAR_pre50	149	15.417	13.743	7.233	14.331	21.174	-15.890	79.440
CAR_total	153	-0.309	7.060	-3.769	-0.777	2.960	-35.938	37.424
Cover	157	10.089	6.555	5.000	11.000	15.000	0.000	27.000
SSA_max	157	0.280	0.622	0.000	0.000	0.450	0.000	3.550
Size	146	0.005	0.006	0.002	0.002	0.003	0.000	0.023
Turn	138	0.004	0.002	0.002	0.003	0.005	0.000	0.012
WZ_scaled	137	3.638	3.138	1.603	2.680	4.260	0.373	19.663

Table 2 (Panel B). Summary statistics, Deletions (N=147).

variable	N	Mean	SD	P25	Median	P75	Min	Max
CAR_ann	145	-0.246	4.428	-2.326	0.094	1.801	-22.761	14.902
CAR_eff	145	-0.720	4.936	-2.624	-0.857	1.177	-15.422	27.944
CAR_pre50	144	-10.872	17.511	-20.455	-10.131	-1.294	-69.413	62.995
CAR_total	145	-0.917	9.112	-4.218	-0.034	3.929	-36.675	28.102
Cover	147	11.503	6.840	7.000	13.000	17.000	0.000	25.000
SSA_max	147	0.836	1.102	0.000	0.600	1.245	0.000	6.820
Size	145	0.005	0.011	0.001	0.002	0.004	0.000	0.085
Turn	137	0.005	0.004	0.003	0.004	0.006	0.000	0.034
WZ_scaled	135	4.389	4.088	2.057	3.461	5.228	0.364	27.060

Table 2 (Panel C). Summary statistics, Pooled (N=304).

variable	N	Mean	SD	P25	Median	P75	Min	Max
CAR_ann	298	-0.036	3.894	-1.751	0.059	1.770	-22.761	14.902
CAR_eff	298	-0.189	4.337	-2.056	-0.198	1.346	-15.422	27.944
CAR_pre50	293	2.497	20.475	-9.944	3.002	15.456	-69.413	79.440
CAR_total	298	-0.605	8.115	-4.088	-0.375	3.188	-36.675	37.424
Cover	304	10.773	6.721	5.000	12.000	16.000	0.000	27.000
SSA_max	304	0.549	0.928	0.000	0.000	0.723	0.000	6.820
Size	291	0.005	0.008	0.002	0.002	0.004	0.000	0.085
Turn	275	0.004	0.003	0.003	0.004	0.005	0.000	0.034
WZ_scaled	272	4.011	3.654	1.840	3.036	4.737	0.364	27.060

3.3 Empirical methodology

The cross-sectional test of the primary hypothesis takes the form

$$CAR_i = \alpha + \beta_1 SSA + \gamma' X_i + \varepsilon_i \tag{3}$$

where X is a vector of controls: log Size, Turn, WZ, Cover, and a fixed effect for the index i (1[FTSE]). For Additions, the direction prediction is $\beta < 0$, under the cushioning hypothesis, as short sellers who anticipate mechanical buying by index funds can sell short ahead of ED, supplying shares and dampening upward price pressure. Accordingly, stocks with higher disclosed short interest should rise less. For Deletions, the direction prediction is $\beta < 0$ too, under what we call the compounding hypothesis, as higher disclosed short interest during [AD, ED] captures SSA concentrated in the period when index funds are forced to sell. Its association with more negative deletion CARS, and the fading of this association as the index effect itself disappears, is the central test of this paper. Because the EU SSR censors observations below 0.5%, the directional test is conservative: any short-selling activity below the threshold goes unobserved, biasing the estimate toward zero. Therefore, a statistically significant negative coefficient constitutes a demanding test.

Equation (3) is estimated separately for additions and deletions, and then pooled with a Type indicator and an SSA × Type interaction to test for asymmetry. Following Nagel (2005), the deletion side is expected to be where short-sellers' constraints bind most tightly, as prices on the downside most require arbitrageurs to cushion mispricing. Equation (3) is also estimated with sub-period dummies (early sub-period 2013–2017 versus late sub-period 2018–2026) and with an SSA × Late interaction, motivated by the Greenwood-Sammon prediction that the index effect, and thus the role for short-sellers in cushioning the addition effect and in compounding the deletion effect should be larger in the earlier years of the sample.

All cross-sectional regressions employ heteroskedasticity-consistent (HC1) standard errors. Clustering standard errors by event date was initially considered due to the concentration of EURO STOXX 50 reconstitution dates in September; however, this concern is mitigated in the pooled sample because the FTSE 100's quarterly schedule and the inclusion of 246 FTSE events distribute the dates more evenly across the sample window. Accordingly, HC1 standard errors are reported as the primary specification, with event-date clustering noted where relevant.

4. Results

4.1 Mean CARs

Table 3 reports mean cumulative abnormal returns by sample, event type, and window with t-tests against zero. The pooled announcement-window CAR is statistically indistinguishable from zero for both additions (+0.16%, t = 0.61) and deletions (-0.25%, t = -0.67). The effective-window CAR for pooled deletions is marginally negative (-0.72%, t = -1.76, p = 0.08) but insignificant at the 5% level. The total-window CAR is similarly small in absolute value and statistically insignificant: -0.31% for additions and -0.92% for deletions. On average across the 304 events, there is essentially no detectable index-inclusion effect. This extends to a European setting the disappearance Greenwood and Sammon (2025) document for the U.S.

The pooled null reflects two distinct underlying patterns: a residual STOXX 50 deletion effect and a fully absent FTSE 100 effect, which average to near zero in the pooled sample. In the EURO STOXX 50, deletions still show a marginally significant negative announcement CAR (-1.49%, t = -1.93, p = 0.06); STOXX additions show a positive but insignificant CAR (+0.68%, t = 1.20). In the FTSE 100, neither additions nor deletions show any detectable announcement effect (CARs of 0.03% and +0.04%, both with |t| < 0.10). The contrast between the two indexes is consistent with their reconstitution methodologies: the FTSE 100 is fully rule-based and almost perfectly anticipated (Beneish and Whaley, 1996), so any price reaction to a forthcoming change would be priced in well before the official announcement; the EURO STOXX 50 is partly discretionary, and the announcement still conveys some information.

A complementary conjecture, which we do not test here, is that FTSE 100 constituents' size and liquidity make the mechanical fund demand too small a fraction of daily float to move prices materially. The pooled-deletion total CAR of −0.92% is smaller in magnitude than Shleifer's (1986) original +2.8% and consistent with Greenwood–Sammon's reported < 1% for the recent decade. The pooled average is indistinguishable from zero, but the sub-period and cross-sectional analysis below will reveal important heterogeneity. This heterogeneity motivates the paper's focus on the sub-period and cross-sectional SSA regressions that follow.

Table 3. Mean cumulative abnormal returns by sample, event type, and window.

Sample	Group	Window	N	Mean (%)	t-stat	p-value
STOXX50	Additions	CAR_ann	31	0.679	1.20	0.240
STOXX50	Additions	CAR_eff	31	0.901	1.28	0.209
STOXX50	Additions	CAR_total	31	1.255	1.28	0.209
STOXX50	Deletions	CAR_ann	27	-1.488*	-1.94	0.063
STOXX50	Deletions	CAR_eff	27	-0.768	-0.97	0.341
STOXX50	Deletions	CAR_total	27	-1.874	-0.99	0.330
FTSE100	Additions	CAR_ann	122	0.031	0.10	0.919
FTSE100	Additions	CAR_eff	122	0.164	0.51	0.610
FTSE100	Additions	CAR_total	122	-0.707	-1.06	0.292
FTSE100	Deletions	CAR_ann	118	0.038	0.09	0.926

Sample	Group	Window	N	Mean (%)	t-stat	p-value
FTSE100	Deletions	CAR_eff	118	-0.709	-1.50	0.135
FTSE100	Deletions	CAR_total	118	-0.698	-0.84	0.400
Pooled	Additions	CAR_ann	153	0.162	0.61	0.546
Pooled	Additions	CAR_eff	153	0.314	1.07	0.287
Pooled	Additions	CAR_total	153	-0.309	-0.54	0.589
Pooled	Deletions	CAR_ann	145	-0.246	-0.67	0.505
Pooled	Deletions	CAR_eff	145	-0.72*	-1.76	0.081
Pooled	Deletions	CAR_total	145	-0.917	-1.21	0.228

Figure 3. Average cumulative abnormal returns in event time (+/-30 trading days). Shaded bands: 95% confidence intervals.

Market-adjusted CARs. Shaded band: +/-1.96 SE. Dotted line: announcement date.

Both indexes exhibit pre-announcement price pressure in the expected directions. For additions, returns begin rising approximately 30 trading days before the announcement, with FTSE 100 additions reaching about +10%, and STOXX 50 additions following a similar trajectory, with similar dispersion. For deletions, prices drift downward well in advance of the announcement rather than falling sharply at the AD. After the announcement, returns stabilize in both indexes, with a small reversal observed for STOXX 50 consistent with the Lynch–Mendenhall (1997) pattern of temporary price pressure unwinding once mechanical rebalancing is complete.

Both indexes display systematic pre-announcement drift (Figure A4): additions rise continuously over the 100 trading days before AD, while deletions drift downward. This is consistent with both predictability (smart money front-running (Beneish and Whaley, 1996) and reverse selection (index committees selecting winners). This pattern represents the empirical signature of perfect anticipation. The large pre-announcement drift in both directions (mean CAR_pre50 = +15.4% for additions, -10.9% for deletions) is consistent with the front-running evidence in Figure A4. Having established the basic result, we now turn to whether the two indexes are sufficiently similar to be pooled.

Table 4 stratifies the mean CARs by sub-period (2013–2017, 2018–2021, 2022–2026) to test the Greenwood-Sammon prediction that the index effect should weaken over time. The early-period evidence is consistent with a non-trivial index effect on both sides. On the addition side, STOXX 50 effective and total CARs are +1.69% (t = 2.54) and +4.20% (t = 2.72) respectively; pooled additions show a +0.67% announcement CAR (t = 2.24). On the deletion side, the STOXX 50 total CAR is −7.7% (t = −2.00), FTSE 100 effective CAR is −1.20% (t = −2.09), and pooled deletion effective and total CARs are −1.45% (t = −2.68) and −2.52% (t = −2.15).

This mostly dissipates in the middle sub-period (2018-2021), with only the Euro STOXX 50 deletion announcement window retaining marginal significance (-2.56%, t = -1.99). In the late sub-period (2022-2026), no CAR is statistically distinguishable from zero. This is precisely the disappearing index effect documented by Greenwood and Sammon (2025), now extended to European blue-chip indexes.

Table 4. Mean CARs by sub-period, sample, and event type.

Sub-period	Index	Type	N	Ann (%)	t (Ann)	Eff (%)	t (Eff)	Total (%)	t (Total)
2013–2017	FTSE100	Addition	43	0.564**	2.227	-0.355	-1.144	-0.742	-1.209
2013–2017	FTSE100	Deletion	42	-0.378	-0.697	-1.198**	-2.092	-1.514	-1.317
2013–2017	Pooled	Addition	51	0.666**	2.236	-0.028	-0.092	0.048	0.078
2013–2017	Pooled	Deletion	50	-0.612	-1.170	-1.449**	-2.675	-2.519**	-2.145
2013–2017	STOXX50	Addition	8	1.2	0.880	1.693**	2.542	4.196**	2.723
2013–2017	STOXX50	Deletion	8	-1.811	-1.120	-2.739	-1.753	-7.666*	-2.001
2018–2021	FTSE100	Addition	39	-0.248	-0.292	0.822	0.902	-0.535	-0.290
2018–2021	FTSE100	Deletion	38	0.513	0.500	-0.042	-0.034	-0.131	-0.067
2018–2021	Pooled	Addition	52	0.094	0.144	0.855	1.109	-0.277	-0.194
2018–2021	Pooled	Deletion	49	-0.19	-0.221	-0.111	-0.113	-0.502	-0.318
2018–2021	STOXX50	Addition	13	1.04	1.589	0.948	0.630	0.438	0.245
2018–2021	STOXX50	Deletion	11	-2.555*	-1.993	-0.346	-0.250	-1.75	-0.762
2022–2026	FTSE100	Addition	43	-0.239	-0.568	0.145	0.363	-0.839	-0.879
2022–2026	FTSE100	Deletion	39	-0.026	-0.048	-0.824	-1.390	-0.477	-0.394
2022–2026	Pooled	Addition	53	-0.233	-0.586	0.156	0.433	-0.687	-0.848
2022–2026	Pooled	Deletion	47	0.029	0.061	-0.578	-1.118	0.242	0.210
2022–2026	STOXX50	Addition	10	-0.207	-0.182	0.205	0.233	-0.037	-0.027
2022–2026	STOXX50	Deletion	8	0.301	0.332	0.622	0.710	3.749	1.164

4.2 Pooling Tests

Prior to estimating equation (3) on the pooled sample, the suitability of combining the two indexes is tested using three approaches. First, Welch's t-tests are conducted on the difference in mean CAR between the two indexes for each window. Second, a Chow test of the cross-sectional regression in equation (3) formally assesses whether all coefficients (the intercept and slopes) are equal across the two sub-samples.

The Chow F-statistic is $F =$

$$F = \frac{\left[\frac{SSR_P - SSR_U}{k}\right]}{\left[\frac{SSR_U}{N-2k}\right]} \qquad (4)$$

Where SSRP is the pooled (restricted) sum of squared residuals, and SSRU is the sum of squared residuals when the regression is run separately on the two indexes, k is the number of parameters, and N is the total sample size. Third, an SSA × Index interaction is included in the pooled regression to test whether the marginal effect of disclosed short interest on CAR differs across indexes. If the null hypothesis of pooling cannot be rejected in any of these tests, equation (3) is estimated on the pooled 304-event sample with an Index fixed effect to absorb level differences.

Welch's t-tests on the differences in mean CAR between the two indexes find no statistically significant differences for any window (Table A1). The t-statistics range from -0.67 to +0.64 across windows, with p-values between 0.51 and 0.67. Levene's tests of variance equality also fail to reject the null of equality (Table A1). Means and variances of the firm-level controls do differ: STOXX firms are substantially larger than FTSE firms in market capitalization, have lower analyst coverage, and slightly lower arbitrage risk. These differences are absorbed by the standard controls in equation (3) and, additionally, by the index fixed effect.

The Chow F-statistics are 0.627, 1.104, and 1.441 across the announcement, effective, and total windows respectively (df = 6, 255), with p-values of 0.71, 0.36, and 0.20. We cannot reject parameter equality at conventional levels in any of the three windows. No individual interaction coefficient in a pooled regression with full Index × Control interactions is significant at the 5% level. The formal Chow test results are in Table 5. The results do not reject the null hypothesis of parameter equality at conventional significance levels, and pooled regressions are accordingly estimated with an index fixed effect to account for residual level differences.

Table 5. *Chow test for parameter equality across the EURO STOXX 50 and FTSE 100 sub-samples in the cross-sectional CAR regression of equation (3). Under the null, the F-statistic follows F (k, N - 2k). Failing to reject implies that the regression coefficients are statistically indistinguishable across indexes.*

window	**F**	**df1**	**df2**	**p_value**	**N**	**SSR_pooled**	**SSR_unres**
CAR_ann	0.627	6	255	0.709	267	3,725	3,671
CAR_eff	1.104	6	255	0.360	267	5,017	4,890
CAR_total	1.441	6	255	0.199	267	17,594	17,017

Failure to reject is a necessary but not sufficient condition for homogeneous treatment effects. Accordingly, we report index-separate regressions in the appendix (Tables A3 and A5) alongside the pooled specifications.

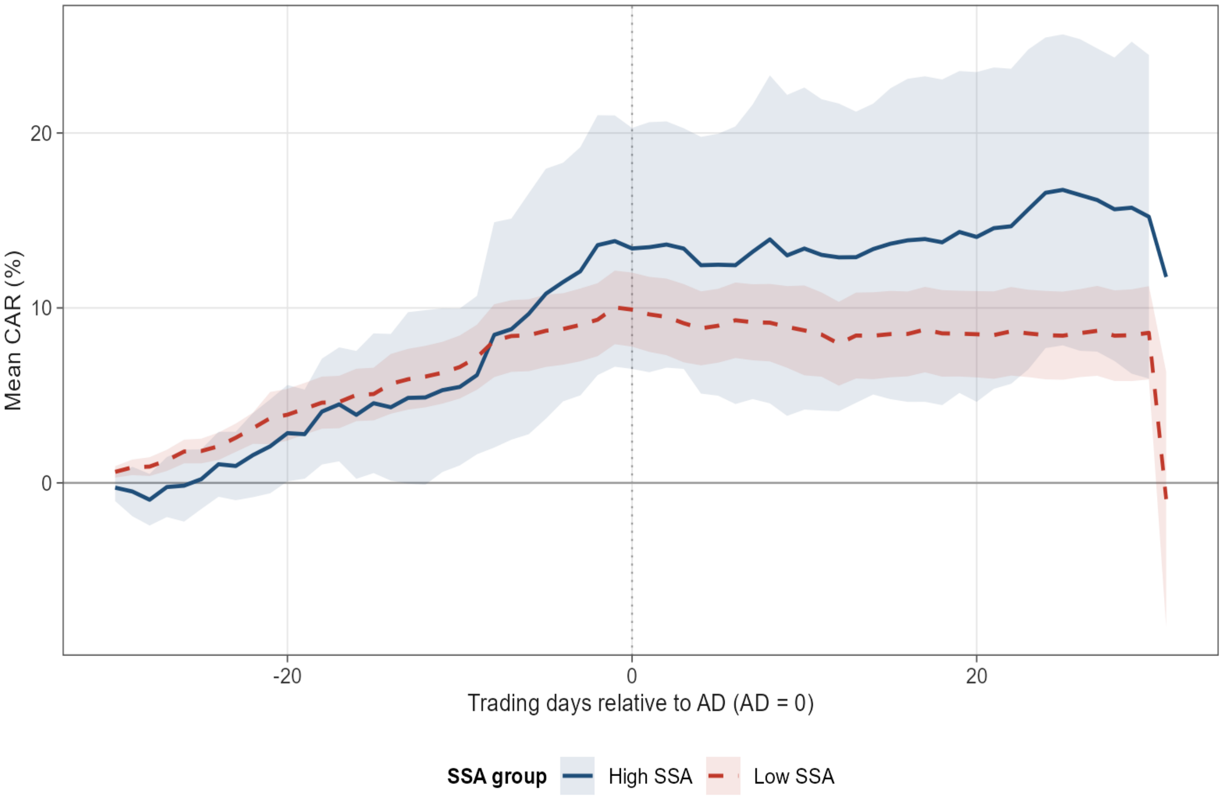
4.3 Addition Cross-Section Analysis

4.3.1 Univariate Evidence

The addition-side cross-sectional analysis tests the cushioning hypothesis: stocks with higher disclosed short interest during the total window should display lower CARs around the index inclusion. We begin with univariate evidence (4.3.1), proceed to a multivariate baseline (4.3.2) and sub-period split (4.3.3), test the arbitrage-risk channel (4.3.4), and probe sensitivity to the event window (4.3.5).

We begin the additional-side analysis with a note on statistical power: only 38 of the 157 addition events carry disclosed short position during [AD, ED]. Figure 4 plots event-time CARs for High-SSA (SSA_max above the median of the disclosed sub-sample at 0.74%) and Low-SSA over the ±30-day window around the announcement. The confidence bands overlap throughout the window, but the High-SSA series in fact sits above the Low-SSA series during the pre-event run-up, the opposite of what the cushioning hypothesis predicts.

Figure 4. Event-time CARs: High-SSA vs. Low-SSA additions (±30 days). Shaded band: ±1.96 SE.



Additions only. High SSA = SSA_max above median of disclosed sub-sample (0.735%). Shaded band: ±1.96 SE.

Figure 5 reports the time path of disclosed short interest, conditional on at least one holder above the threshold. FTSE 100 additions display a stable disclosed short interest across the [AD, AD+25] window, while the Euro STOXX 50 additions, in contrast, exhibit a sharp spike on AD and then a noisy oscillation between 0.5% and 1.4%. The pattern is consistent with arbitrageurs reacting to the STOXX 50's partly discretionary methodology, where the announcement carries more news content than under the rule-based FTSE 100 process, though the STOXX 50 sub-sample is small. The figure alone cannot distinguish cushioning from speculative front-running.

Figure 5. Mean disclosed net short interest around addition events (SSA_any = 1).

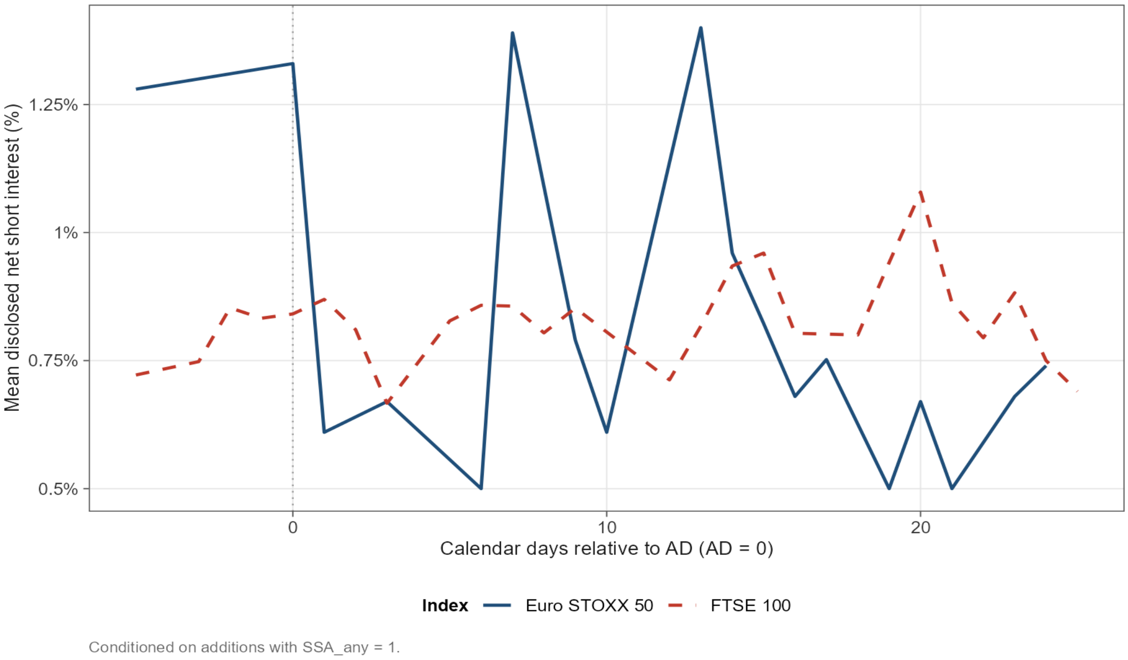


Table 6 stratifies addition CARs by SSA group and sub-period. The full-sample shows essentially no difference in mean CARs between High-SSA and Low-SSA additions in any window. The early-period (2013–2017) High-SSA cell reports a +3.80% total-window CAR, but only with n = 2 events. The 2018–2026 sub-period, where the disclosed sub-sample is concentrated (n = 17 High-SSA, 78 Low-SSA), shows a −0.33% total-window mean for High-SSA against −0.11% for Low-SSA. This difference of 0.22 percentage points is statistically and economically negligible.

Table 6. Addition CARs by SSA group and sub-period. High SSA = SSA_max above median of disclosed sub-sample (0.735%). Stars indicate significance vs. zero.

sub_period	**SSA_group**	**N**	**Ann**	**t (Ann)**	**Eff**	**t (Eff)**	**Total**	**t (Tot)**
2013–2017	High SSA	2	1.835	1.275	0.124	1.671	3.795	1.169
2013–2017	Low SSA	35	0.487	1.423	-0.025	-0.067	-0.182	-0.242
2018–2026	High SSA	17	-0.184	-0.229	-0.635	-0.698	-0.331	-0.149
2018–2026	Low SSA	78	0.257	0.646	0.761	1.567	-0.111	-0.123
Full sample	High SSA	19	0.028	0.038	-0.555	-0.682	0.103	0.051
Full sample	Low SSA	113	0.328	1.119	0.518	1.461	-0.133	-0.200

In Table 7, the bivariate regression, the SSA coefficient on the effective window is -0.647*, the only result that approaches conventional significance. This provides suggestive evidence in the predicted direction, but does not sustain strong inference, likely due to the limited disclosed positions.

Table 7. Bivariate: CAR ~ SSA_max, additions only. HC1 SEs in italics.

Term	(1) Ann	(2) Eff	(3) Total
(Intercept)	0.381	0.569	0.001
	(0.304)	*(0.365)*	*(0.703)*
SSA_max	-0.303	-0.647*	-0.316
	(0.434)	*(0.374)*	*(0.830)*
N	132	132	132
R^2	0.004	0.013	0.001

4.3.2 Multivariate Baseline

Table 8 shows CAR regressed on SSA_max, log Size, Turn, WZ, Cover, and an index fixed effect. Throughout each of the 3 windows, the SSA coefficient is negative and consistent in sign with the cushioning hypothesis but does not reach the 5% level in any case. The effective-window coefficient, -0.841, is largest in magnitude, and implies each additional percentage point of disclosed short interest is associated with a 0.84 percentage point reduction in abnormal return of an addition, conditional on the other controls. To benchmark this magnitude: the mean early-period pooled addition CAR was +0.67%, so the -0.841 coefficient implies that a stock at the 75th percentile of SSA_max (0.45%) would experience an addition CAR roughly 38 basis points lower than an otherwise identical stock with no disclosed short interest. The is_FTSE coefficient on the announcement window is -3.823**, and significant at the 5% level. This reflects lower announcement-day CARs on the FTSE100 documented in table 3, consistent with its anticipation. The SSA continues to be negative and short of conventional significance.

Table 8. Multivariate: CAR ~ SSA_max + controls, additions only. HC1 SEs in italics.

Term	(1) Ann	(2) Eff	(3) Total
(Intercept)	4.696***	-1.410	3.877
	(1.731)	*(2.986)*	*(4.362)*
SSA_max	-0.288	-0.841	-0.630
	(0.490)	*(0.513)*	*(1.099)*
Size	-285.596***	97.316	-303.893
	(106.713)	*(215.200)*	*(310.089)*
Turn	100.036	494.663	807.485
	(163.745)	*(350.098)*	*(639.596)*
WZ_scaled	-0.145	-0.171	-0.154

Term	(1) Ann	(2) Eff	(3) Total
	(0.094)	*(0.128)*	*(0.232)*
Cover	0.023	-0.029	-0.075
	(0.049)	*(0.066)*	*(0.165)*
is_FTSE	-3.823**	0.748	-5.117
	(1.554)	*(2.656)*	*(4.083)*
N	132	132	132
R²	0.063	0.075	0.058

4.3.3 Sub-period Stratification

Table 9 extends the baseline specification by interacting SSA_max with an indicate for the late sub-period (2018-2026). The early period SSA slope is positive and insignificant across all three windows, and the interaction term SSA_max:is_late is negative in all three windows, indicating the SSA-CAR relationship became more negative overtime for additions. The effective-window interaction is -1.762** and the total-window interaction is -2.619*, both significant or marginally significant. Two interpretations are consistent with this pattern. Under the first, short sellers on the addition side shifted from a neutral stance in the early period, when the addition CAR was positive and covered quickly, to a more active role in the late period when, paradoxically, the CAR had already collapsed to zero. Under the second, the interaction is a compositional artifact: late-period additions are drawn from a different sector distribution or liquidity regime, and SSA proxies for these unobserved characteristics rather than reflecting a genuine change in short-seller behavior. Distinguishing between these requires more granular intra-window position data than is available under the EU SSR.

Table 9. Sub-period interaction on additions. SSA_max = early-period slope; SSA_max:is_late = change in slope for 2018–2026. HC1 SEs in italics.

Term	(1) Ann	(2) Eff	(3) Total
(Intercept)	4.772***	-2.134	4.321
	(1.763)	*(3.010)*	*(4.640)*
SSA_max	0.333	0.364	1.175
	(0.351)	*(0.398)*	*(1.023)*
is_late	-0.176	0.676	-0.772
	(0.541)	*(0.632)*	*(1.298)*
SSA_max:is_late	-0.903	-1.762**	-2.619*
	(0.644)	*(0.762)*	*(1.538)*
Size	-290.155***	108.961	-322.381
	(107.590)	*(215.036)*	*(314.850)*
Turn	137.671	510.987	931.301
	(168.814)	*(363.545)*	*(654.673)*

Term	(1) Ann	(2) Eff	(3) Total
WZ_scaled	-0.133	-0.168	-0.113
	(0.095)	*(0.124)*	*(0.242)*
Cover	0.014	-0.038	-0.101
	(0.049)	*(0.067)*	*(0.166)*
is_FTSE	-3.820**	1.083	-5.194
	(1.581)	*(2.675)*	*(4.299)*
N	132	132	132
R^2	0.073	0.096	0.076

4.3.4 Arbitrage-Risk Channel

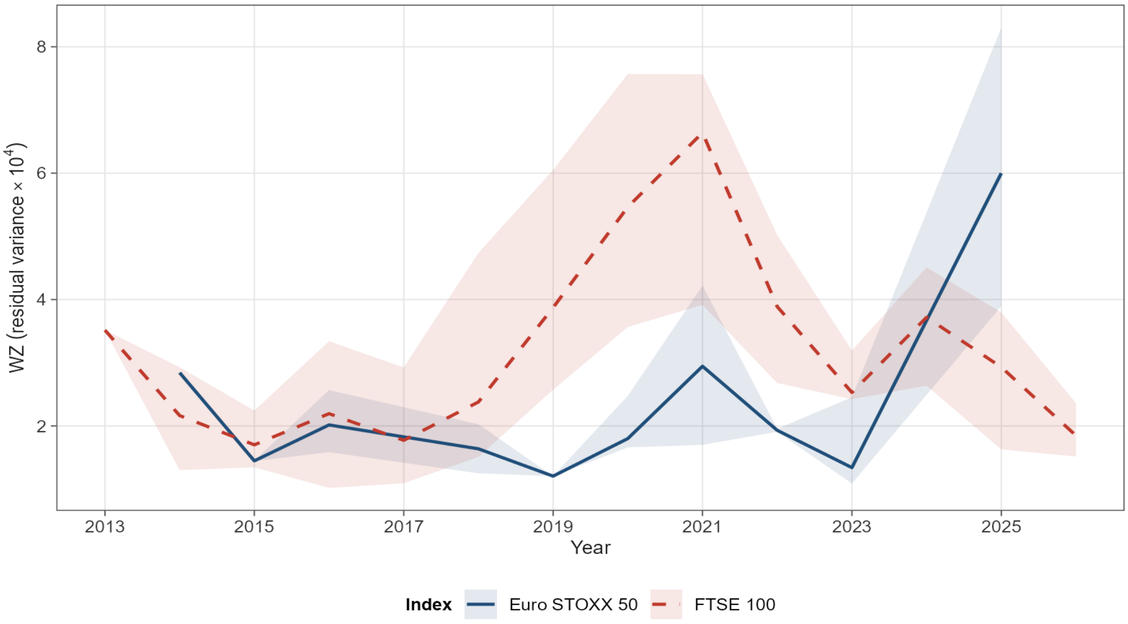
Table 10 introduces the arbitrage-risk channel test, adding WZ_scaled and its interaction with SSA_max. On the effective window, SSA_max:WZ_scaled is -0.348***, significant at the 1% level. The attenuation effect of disclosed short interest on CARs is substantially larger for stocks with higher idiosyncratic variance, exactly where the limits-to-arbitrage framework (Wurgler and Zhuravskaya, 2002) predicts demand curves to slope more steeply. The effective-window R^2 rises from 0.075 in the baseline to 0.116 with the interaction, indicating meaningful incremental fit. Since the announcement and total windows interaction is near zero and insignificant, the effect-window result is the most informative for the arbitrage-risk channel on the addition side. It shows that where short-selling activity is high and the stock is hard to hedge, the price response to mechanically generated demand is more greatly attenuated, consistent with Aghaee's (2022) channel identification.

Table 10. Arbitrage-risk channel, additions. HC1 SEs in italics..

Term	(1) Ann	(2) Eff	(3) Total
(Intercept)	4.747***	-1.584	3.910
	(1.759)	*(2.947)*	*(4.401)*
SSA_max	-0.729	0.673	-0.916
	(0.699)	*(0.528)*	*(1.601)*
WZ_scaled	-0.188	-0.025	-0.181
	(0.116)	*(0.077)*	*(0.215)*
SSA_max:WZ_scaled	0.101	-0.348***	0.066
	(0.113)	*(0.107)*	*(0.341)*
Size	-280.273**	79.051	-300.439
	(107.936)	*(211.724)*	*(313.206)*
Turn	96.259	507.622	805.035
	(168.944)	*(337.850)*	*(648.229)*
Cover	0.022	-0.026	-0.076

Term	(1) Ann	(2) Eff	(3) Total
	(0.050)	*(0.064)*	*(0.166)*
is_FTSE	-3.710**	0.362	-5.044
	(1.569)	*(2.617)*	*(4.104)*
N	132	132	132
R²	0.068	0.116	0.059

Figure 6. WZ arbitrage-risk measure by year, additions only (cross-sectional median + IQR band).



Additions only. Median and IQR. Window: [AD−250, AD−1].

4.3.5 Robustness

The addition-side results are robust to changes in the event window and variable construction. Extending the announcement windows [AD-5, AD+5] shows positive and significant SSA coefficient (Table A2: 1.978***). This window likely captures the pre-announcement price run-up during which the high-SSA stocks already experienced substantial appreciation. Over the post-effective window [ED, ED+5], the SSA coefficient is -0.605*, significant at the 10% level (Table A2), consistent with short-sellers covering positions after the effective date and contributing to price recovery.

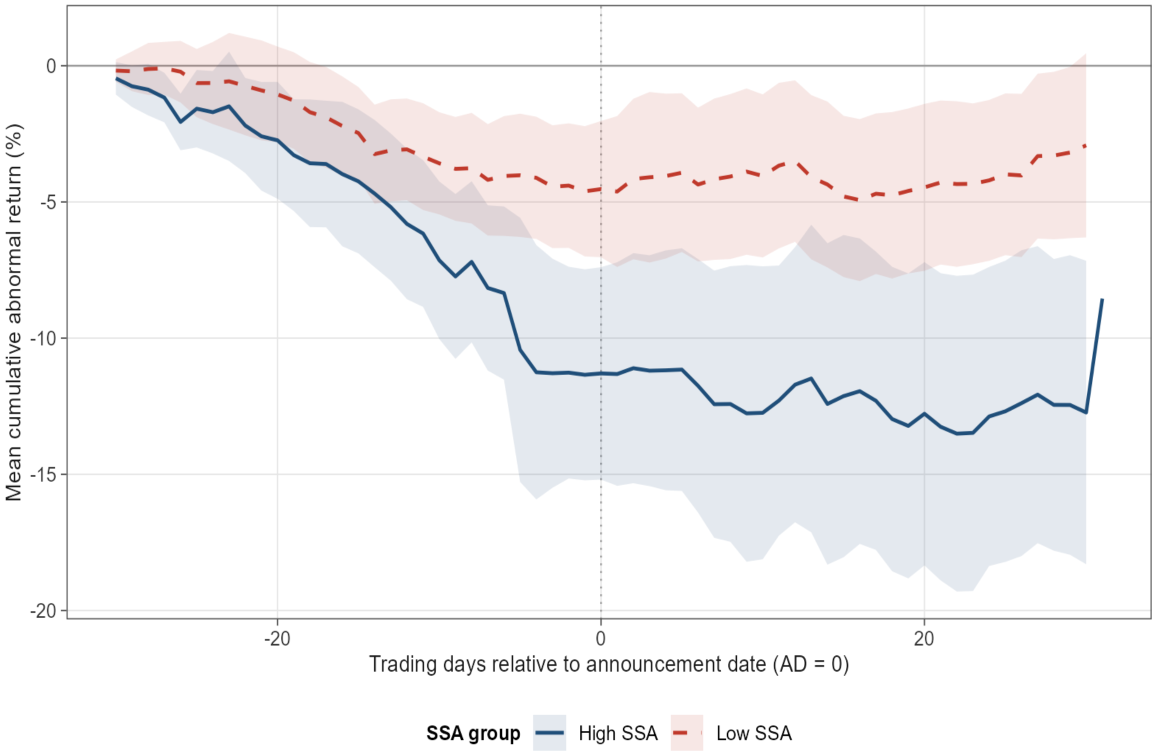
4.4 Deletion Cross-Section Analysis

4.4.1 Univariate Evidence

The deletion-side cross-sectional analysis test the compounding hypothesis, stocks with higher disclosed short interest during the total window should display more negative CARs around the index deletion. This is because short sellers add supply alongside the mechanical index-fund selling. The structure mirrors the addition side - univariate (4.4.1), multivariate baseline (4.4.2), sub-period split (4.4.3), arbitrage-risk channel (4.4.4), and window sensitivity (4.4.5).

Figure 7 shows High-SSA deletions experience CARs roughly three times more negative than Low-SSA deletions at the end of the event, with the gap opening sharply around the announcement date. This visual evidence is in the direction of the compounding hypothesis that deletions accompanied by larger disclosed short positions experience larger price drops.

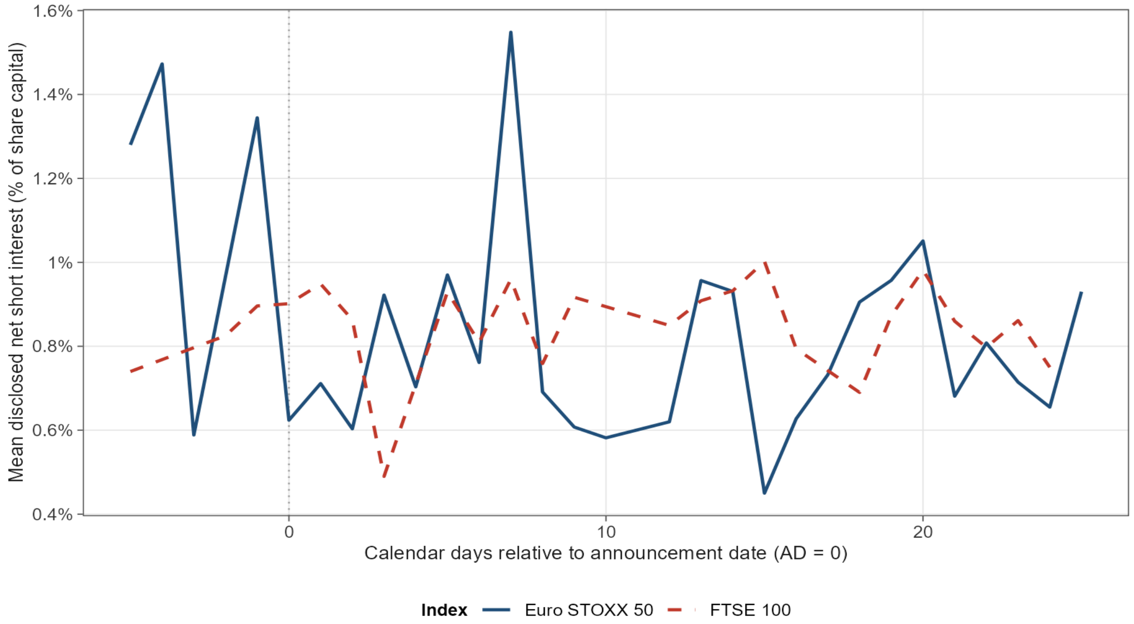
Figure 7. Event-time cumulative abnormal returns for High-SSA vs. Low-SSA deletion events (+/-30 trading days). Shaded band: +/-1.96 SE.



Deletion events only. High SSA = SSA_max above median of disclosed sub-sample (0.955%). Shaded band: ±1.96 SE.

Figure 8 shows that disclosed short interest on STOXX 50 deletions rises sharply in the week before AD and remains elevated through the event window, while FTSE 100 deletions show a flatter trajectory. The pattern is consistent with the partly discretionary STOXX 50 methodology leaving more room for informed positioning ahead of the announcement than the rule-based FTSE 100, as well as the smaller sample size increasing volatility.

Figure 8. Mean disclosed net short interest around deletion events (SSA_any = 1).



Conditioned on deletion events with at least one holder above the 0.5% EU SSR threshold.

In Table 11, 2013–2017, High-SSA deletions experienced an average total-window CAR of −5.54% (t = −1.93, n = 13), while Low-SSA deletions averaged +0.06%. The univariate gap of roughly 5.6 percentage points is in the predicted direction of the compounding hypothesis, large in magnitude, and concentrated in the sub-period where the deletion CAR is itself largest.

Table 11. Mean deletion CARs by SSA group and sub-period. High SSA = SSA_max above median of disclosed sub-sample (0.955%). Low SSA = at or below median (incl. zero). t-stat and stars vs zero.

sub_period	SSA_group	N	Ann	t_ann	Eff	t_eff	Total	t_tot
2013–2017	High SSA	13	-0.664	-0.666	-2.575*	-2.033	-5.538*	-1.926
2013–2017	Low SSA	28	-0.341	-0.466	-0.311	-0.573	0.063	0.051
2018–2026	High SSA	30	0.213	0.253	0.859	0.564	0.837	0.371
2018–2026	Low SSA	64	-0.125	-0.205	-0.896**	-2.158	-0.377	-0.384
Full sample	High SSA	43	-0.052	-0.080	-0.179	-0.156	-1.091	-0.594
Full sample	Low SSA	92	-0.191	-0.399	-0.718**	-2.160	-0.243	-0.313

The bivariate regression of CAR on SSA_max for deletions (Table 12) provides the baseline benchmark for which the multivariate results are interpreted. The estimate slope is positive across both announce and effective windows, but negative for the total. While not completely consistent with the hypothesis that disclosed short interest compounds the price drop, the magnitude of the largest window is directionally in line. This reflects SSA_max capturing short-selling in their selling phase over the total window, adding supply alongside the mechanical index-fund selling. However, the precision is low, and this is expected for two reasons. Firstly, the index effect itself has largely disappeared over the time sample, leaving limited cross-sectional variation in CAR for any variable to explain. Secondly, the SSA is left-censored at the 0.5% regulatory threshold, so events with true short interest below that are coded as 0, compressing the explanatory variable. Any subsequent price recovery from short-covering falls largely outside the total-window measurement. These limitations motivate moving directly to the multivariate specification and, critically, to the sub-period split in Section 4.4.3, where the variation in deletion CARs is concentrated.

Table 12. Bivariate regressions: CAR ~ SSA_max, deletions only (N = 135). HC1 standard errors in italics.

Term	**(1) Ann**	**(2) Eff**	**(3) Total**
(Intercept)	-0.351	-0.583	0.042
	(0.592)	*(0.392)*	*(0.879)*
SSA_max	0.245	0.044	-0.667
	(0.590)	*(0.499)*	*(0.989)*
N	135	135	135
R^2	0.003	0.000	0.005

4.4.2 Multivariate Baseline

Table 13 reports the multivariate specification, CAR regressed on SSA_max, log Size, Turn, WZ, Cover, and an index fixed effect, estimated for deletions. The SSA_max coefficient is negative in the announcement and total windows (-0.076 and -0.669, respectively), but positive in the effective window (0.345). While the effective window could be short-selling covering, the total window is consistent in sign, but none of these meet the conventional significance thresholds. Therefore, it does not constitute strong evidence for the compounding hypothesis on its own. Cover reaches significance in the announcement and total windows (0.188* and 0.412**, respectively), so deletions of more heavily covered stocks show less negative CARs, consistent with greater prior anticipation reducing the announcement-day drop. Turn is significant in the announcement window (228.561**) and WZ_scaled is significant in the effective window (-0.253**). The variation in deletion CARs needed to identify the effect is concentrated in the early sub-period, as the next section shows.

Table 13. Multivariate: CAR ~ SSA_max + controls, deletions only. HC1 SEs in italics.

Term	**(1) Ann**	**(2) Eff**	**(3) Total**
(Intercept)	-2.997***	0.501	-1.469
	(1.113)	*(1.004)*	*(2.476)*
SSA_max	-0.076	0.345	-0.669
	(0.482)	*(0.472)*	*(0.875)*
Size	-39.762	7.837	-30.082
	(54.680)	*(29.141)*	*(75.705)*
Turn	228.561**	-164.062	-2.985
	(106.883)	*(113.076)*	*(265.589)*

Term	(1) Ann	(2) Eff	(3) Total
WZ_scaled	0.065	-0.253**	-0.215
	(0.122)	*(0.123)*	*(0.280)*
Cover	0.188*	0.052	0.412**
	(0.110)	*(0.066)*	*(0.184)*
is_FTSE	-0.541	-0.083	-2.614
	(1.749)	*(1.332)*	*(3.206)*
N	135	135	135
R^2	0.144	0.075	0.083

4.4.3 Sub-period Stratification

The full-sample multivariate regression conceals an important sub-period pattern. As noted in Section 4.1, the deletion-side index effect is concentrated in the early sub-period (2013–2017). If short-sellers compound the deletion drop, their effect on CAR should be larger precisely when the deletion drop is substantial. To test this, the multivariate regression is re estimated on pooled deletions, including a Late dummy (1 if year ≥ 2018) and an SSA × Late interaction. Table 14 presents the results.

The early-period SSA coefficient on the total window is -2.31* (p = 0.06), economically substantial: each additional percentage point of disclosed short interest in [AD, ED] is associated with a 2.3 percentage point more negative total-window CAR for deletion events in 2013-2017, against a sample mean total-window deletion CAR of -7.7% in that sub-period. The SSA × Late interaction is 2.24. Adding it to the early-period coefficient yields a late-period slope of -0.07, statistically indistinguishable from zero. The pattern is that in 2013-2017, when the deletion-side effect was at its largest, disclosed short interest was associated with larger price drops, and that association attenuated as the index effect itself disappeared.

This finding constitutes the central empirical result of the study. The evidence reframes the original hypothesis to align with the observed data: the negative sign of the early-period coefficient implies that higher disclosed short interest during the total window was associated with more negative deletion CARs during the period when those CARs were large themselves. An interpretation is that short sellers were in an active selling phase during the total window, adding supply to the forced index fund rebalancing. A second interpretation is reverse causality, where events with large, anticipated price drops attracted disclosed short positions prior to ED, so SSA is a predictor of large drops rather than the cause. Either way, the association is present only when the deletion effect is itself large, and it disappears when the effect disappears.

Table 14. Sub-period interaction on deletion-side CAR. SSA_max = early-period slope. SSA_max:is_late = change in slope for late period (2018-2026). HC1 SEs in parentheses.

Term	(1) Ann	(2) Eff	(3) Total
(Intercept)	-3.324**	0.303	-2.073
	(1.306)	*(1.119)*	*(2.581)*

Term	(1) Ann	(2) Eff	(3) Total
SSA_max	-0.271	-0.433	-2.306*
	(0.691)	*(0.526)*	*(1.199)*
is_late	0.551	0.471	1.283
	(1.160)	*(0.888)*	*(1.766)*
SSA_max:is_late	0.272	1.062	2.238
	(0.929)	*(0.724)*	*(1.602)*
Size	-44.096	1.402	-45.459
	(55.107)	*(29.728)*	*(75.271)*
Turn	216.232**	-188.750	-59.069
	(105.112)	*(115.228)*	*(264.292)*
WZ_scaled	0.058	-0.255**	-0.222
	(0.123)	*(0.106)*	*(0.274)*
Cover	0.199*	0.070	0.454**
	(0.110)	*(0.068)*	*(0.179)*
is_FTSE	-0.624	-0.249	-2.991
	(1.759)	*(1.258)*	*(3.095)*
N	135	135	135
R^2	0.151	0.100	0.119

The early-period total-window SSA_max coefficient of −2.306 corresponds to t = −1.92 (SE = 1.199, p = 0.06).

4.4.4 Arbitrage-Risk Channel

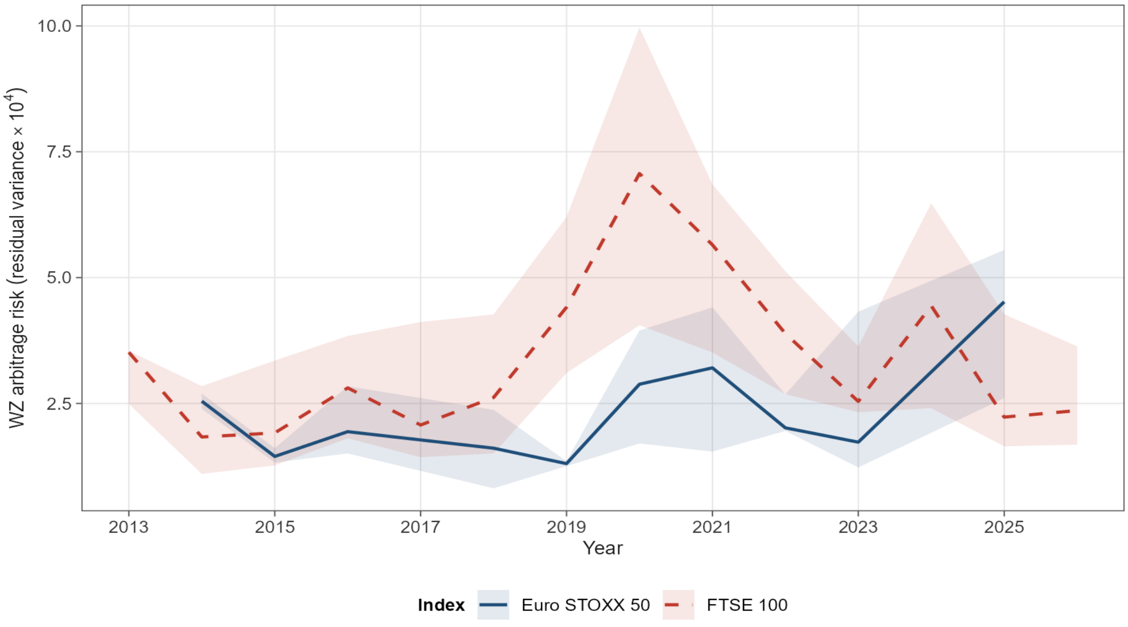
Table 15 introduces the arbitrage-risk channel test for deletions, adding WZ_scaled and its interaction with SSA_max. While negative across all three windows, the SSA_max:WZ_scaled coefficient is -0.137***, significant at the 1% level, in the effective window. This implies that the compounding effect of disclosed short interest on deletion CARs is larger for stocks with higher idiosyncratic variance, consistent with Wurgler-Zhuravskaya (2002) and Aghaee (2022), who predict the demand curve slopes to be steeper where arbitrage risk is greater. The total-window interaction is -0.230 and negative in sign but does not reach conventional significance. Figure 9 plots the cross-sectional median of WZ by year, and both indexes show a marked spike around 2020 corresponding to COVID-19 liquidity stress, with FTSE 100 stocks exhibiting higher arbitrage risk than STOXX 50 stocks throughout the sample.

Table 15. Arbitrage-risk channel test on pooled deletions

Term	(1) Ann	(2) Eff	(3) Total
(Intercept)	-3.066***	-0.345	-2.889
	(1.014)	*(0.992)*	*(2.274)*

Term	(1) Ann	(2) Eff	(3) Total
SSA_max	-0.001	1.256*	0.859
	(0.481)	*(0.740)*	*(1.042)*
WZ_scaled	0.082	-0.050	0.126
	(0.161)	*(0.074)*	*(0.225)*
SSA_max:WZ_scaled	-0.011	-0.137***	-0.230
	(0.084)	*(0.050)*	*(0.141)*
Size	-39.253	14.049	-19.663
	(53.915)	*(28.434)*	*(73.874)*
Turn	226.072**	-194.403**	-53.874
	(113.433)	*(90.846)*	*(228.388)*
Cover	0.189*	0.070	0.442**
	(0.113)	*(0.063)*	*(0.182)*
is_FTSE	-0.567	-0.409	-3.160
	(1.802)	*(1.277)*	*(3.200)*
N	135	135	135
R²	0.144	0.104	0.107

Figure 9. WZ arbitrage-risk measure by year (cross-sectional median + IQR band).



Median and IQR. WZ estimated over [AD-250, AD-1].

4.4.5 Robustness

Several robustness checks confirm the qualitative pattern. First, re-estimating the headline specification over alternative windows ([AD-5, AD+5], [ED, ED+5], and [AD-1, ED+1]) yields a deletion-side SSA coefficient that is negative across all windows in the early sub-period, with significance attained in [AD-5, AD+5] (-2.675*, Table A4).

4.5 Discussion

Our cross-sectional regression measures a conditional correlation, not a causal effect. The primary concern is reverse causality: that CARs drive short-selling rather than the other way around. There are three sub-cases. The first is that price drops on bad news cause holders to hedge or close out long positions by entering short positions, mechanically inducing a positive correlation between disclosed short interest and negative CAR. This concern is partially mitigated by timing: SSA aggregates positions over [AD, ED], while a substantial portion of the total-window CAR is realized after ED, so contemporaneous reverse causality is unlikely to drive the entire result. The second sub-case is that informed short-sellers anticipate a price drop based on fundamental information about the firm, the kind of bad news that may have prompted the index committee to reconsider membership in the first place. To the extent that index changes are based on market capitalization, which is a function of price, this concern is real but should affect both indexes equally. The third sub-case is that disclosure itself is informative; once a holder is identified as having a position above 0.5%, that disclosure may trigger additional selling pressure. We do not have data on intra-window timing of disclosures and cannot directly address this; we note only that a confounder of this kind would, if anything, strengthen the negative association between SSA and deletion CAR (more disclosure → more selling → larger negative CAR).

The Cover coefficient deserves a brief separate note. In Table 13, Cover is positively and significantly associated with deletion CAR in the announcement and total windows, with 0.188* and 0.412** respectively. This translates to deletions of more heavily covered stocks have less negative CARs, suggesting that high analyst coverage is associated with more anticipation, and thus smaller announcement-day drops. This is consistent with a pre-pricing story rather than a information-friction story. Turn is also significant in the deletion announcement window (228.561**, Table 13), which could speak to the float and therefore bid-ask spreads of stocks. The two data limitations worth noting are: firstly, SSA_max is left-censored at 0.5%, biasing all estimated β towards zero, and therefore the compounding effects we observe are conservative lower bonds. Second, our index fixed effect absorbs the average level difference between the two samples but not the higher-order differences in the underlying reconstitution methodology (rule-based vs partly discretionary). Sections 4.2 and 4.3 report results separately by index for transparency, and the qualitative pattern is similar in both, which we take as reassurance that the pooled results are not driven by a particular index's institutional features.

5. Implications and Conclusion

The question this thesis sets out to answer is whether short-selling activity attenuates the abnormal returns associated with stock additions to and deletions from the EURO STOXX 50 and the FTSE 100. Our identifying lever is the EU Short Selling Regulation, which since November 2012 has required public disclosure of net short positions above 0.5% of issued share capital. From those disclosures we build a firm-event measure of disclosed short interest (SSA) and relate it to cumulative abnormal returns. Pooling tests confirm that the EURO STOXX 50 and the FTSE 100 can be combined into a single 304-event sample, more than five times the size of the EURO STOXX 50 alone.

Three findings come out of this exercise. First, the canonical index-inclusion effect that Shleifer (1986) documented and that Greenwood and Sammon (2025) recently showed had disappeared in the U.S. is also absent, on average, in our European data: announcement-window CARs are statistically indistinguishable from zero in both directions. The Greenwood-Sammon disappearance therefore extends to European blue-chip indexes. Second, the residual effect that does remain is concentrated on the deletion side of the EURO STOXX 50 in the earliest sub-period of our sample (2013–2017 mean total-window CAR = -7.7%, t = -2.0, Table 4). The FTSE 100, with its fully rule-based reconstitution methodology, shows no detectable effect in any window. Third, when we split the cross-sectional regression of deletion CAR on SSA before and after 2018, the SSA coefficient is significantly negative in the early period ($\beta = -2.31$, $t = -1.92$, $p = 0.06$) and indistinguishable from zero thereafter. In short: disclosed short-selling activity was associated with larger deletion-side price drops in the early years of the EU SSR, and that association faded along with the deletion effect itself.

The economic reading we take from this is that disclosed short-sellers were compounding the selling pressure from forced index-fund rebalancing during the period when the deletion effect was at its largest, adding supply into an already declining market. As the market's broader capacity to provide liquidity around index events grew (Greenwood and Sammon 2025), the marginal contribution of disclosed short-sellers shrank. This fits the channel logic of Wurgler and Zhuravskaya (2002) and Aghaee (2022): when arbitrage risk falls and the demand-curve slope flattens, fewer arbitrageurs are needed to absorb a given shock, and the ones who do show up have less marginal effect on prices.

Two implications follow for the broader literature. First, the 'disappearing index effect' is not a U.S.-specific phenomenon: we find the same pattern in European blue-chip indexes, which suggests that the disappearance reflects deeper structural changes in market capacity rather than features peculiar to the S&P 500. Second, our findings add direct, position-level evidence to the limits-to-arbitrage framework (Shleifer and Vishny, 1997). In the era when index-effect mispricing was substantial, arbitrageurs whose positions are observable, those above the 0.5% disclosure threshold, were actively compounding the price drop on deletions by selling alongside index funds; as the mispricing has shrunk, so has the compounding. This is the 'adaptive markets' story Greenwood and Sammon (2025) favor: when demand shocks become regular and repeated, competitive markets adapt over time to drive their price impact toward zero.

Several natural extensions of this work suggest themselves. The SSA measure is left-censored, and intra-day or block-level short-selling data, where available, would strengthen the test of $\beta < 0$ by removing the threshold bias. The migration channel of Greenwood and Sammon (2025), paired changes between the EURO STOXX 50 and the EURO STOXX Mid, or between the FTSE 100 and the FTSE 250, would be worth quantifying separately for the European setting. An analysis of the addition side using a sample where the disclosure threshold is lower (the U.S. has no equivalent of the 0.5% rule, but France has historically required reporting at 0.25%) could provide the symmetric test that our addition-side analysis lacks for power reasons. The post-disclosure dynamics of disclosed positions across the event window would help separate the supply-of-shares interpretation from the information-leakage interpretation. Finally, our specification omits a firm-day measure of transaction-cost liquidity. Bid-ask spreads are the standard high-frequency liquidity proxy in the event-study literature and would in principle let us separate the role of disclosed short-sellers from any contemporaneous shift in firm-level trading conditions around index events. We were unable to obtain firm-day bid-ask spreads at the granularity required for our cross-section: the public liquidity series ESMA publishes report only an aggregated, cross-sectional median of the bid-ask price percentage difference across the current EEA30 constituents of STOXX Europe Large 200, an index-level aggregate that cannot be matched to individual reconstitution events (European Securities and Markets Authority, 2023, 2025). The underlying Refinitiv Datastream firm-day quote data on which those aggregates are constructed is not available to us. Future work using a tick-level or order-book dataset (for example Reuters Tick History or LOBSTER) could include a firm-day spread control and test whether the early-period SSA effect on deletion CAR survives once differences in trading liquidity between names are absorbed. We leave these to future work.

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Appendix A: Tables

Table A1. Welch t-tests and Levene F-tests for CAR differences between the Euro STOXX 50 and FTSE 100 sub-samples.

window	n_stoxx	n_ftse	mean_stoxx	mean_ftse	diff	welch_t	welch_p	levene_F	levene_p
CAR_ann	58	240	-0.330	0.035	-0.364	-0.665	0.508	0.189	0.664
CAR_eff	58	240	0.124	-0.265	0.389	0.644	0.521	0.088	0.767
CAR_total	58	240	-0.202	-0.702	0.501	0.431	0.667	0.073	0.788

Table A2 Robustness: alternative windows, additions (N=132). HC1 SEs in italics.

Term	CAR [AD-5,AD+5]	CAR [ED,ED+5]
(Intercept)	10.455**	-0.616
	(4.280)	*(2.222)*
SSA_max	1.978***	-0.605*
	(0.590)	*(0.363)*
SSA_max:is_late	-0.368	-0.031
	(1.527)	*(0.566)*
is_late	-0.935	-0.002
	(1.068)	*(0.741)*
Size	-601.884**	20.268
	(243.107)	*(131.709)*
Turn	17.488	395.247**
	(358.084)	*(190.212)*
WZ_scaled	-0.250	-0.069
	(0.190)	*(0.078)*
Cover	-0.204*	0.024
	(0.107)	*(0.058)*
is_FTSE	-4.377	0.223
	(3.934)	*(1.938)*
N	132	132
R²	0.139	0.050

Table A3. Index-separate additions (N≈27 STOXX; N≈105 FTSE). No index FE. HC1 SEs in italics.

Term	STOXX Ann	STOXX Eff	STOXX Total	FTSE Ann	FTSE Eff	FTSE Total
(Intercept)	4.992**	-2.396	1.959	0.250	-0.602	-0.211
	(2.162)	*(2.937)*	*(4.594)*	*(1.207)*	*(1.720)*	*(3.276)*

Term	STOXX Ann	STOXX Eff	STOXX Total	FTSE Ann	FTSE Eff	FTSE Total
SSA_max	1.120	-6.943	-6.895	-0.283	-0.738	-0.547
	(1.485)	*(5.789)*	*(8.347)*	*(0.507)*	*(0.539)*	*(1.160)*
Size	-282.322*	171.341	-143.942	110.267	35.195	-651.666
	(141.123)	*(231.642)*	*(318.026)*	*(302.859)*	*(480.010)*	*(842.960)*
Turn	198.721	644.682**	534.411	198.790	461.851	838.510
	(255.406)	*(261.873)*	*(347.864)*	*(209.833)*	*(441.109)*	*(794.732)*
WZ_scaled	-0.605*	-0.227	-0.071	-0.140	-0.148	-0.144
	(0.307)	*(0.312)*	*(0.440)*	*(0.086)*	*(0.145)*	*(0.263)*
Cover	0.143*	-0.050	0.086	-0.030	-0.023	-0.111
	(0.072)	*(0.131)*	*(0.203)*	*(0.052)*	*(0.076)*	*(0.213)*
N	27	27	27	105	105	105
R^2	0.398	0.184	0.111	0.022	0.057	0.054

Table A4. Robustness: Table 8 specification re-estimated on alternative CAR windows. CAR_ad5 = [AD-5, AD+5]; CAR_ed5 = [ED, ED+5]. Deletions only, N=135. HC1 SEs in parentheses.

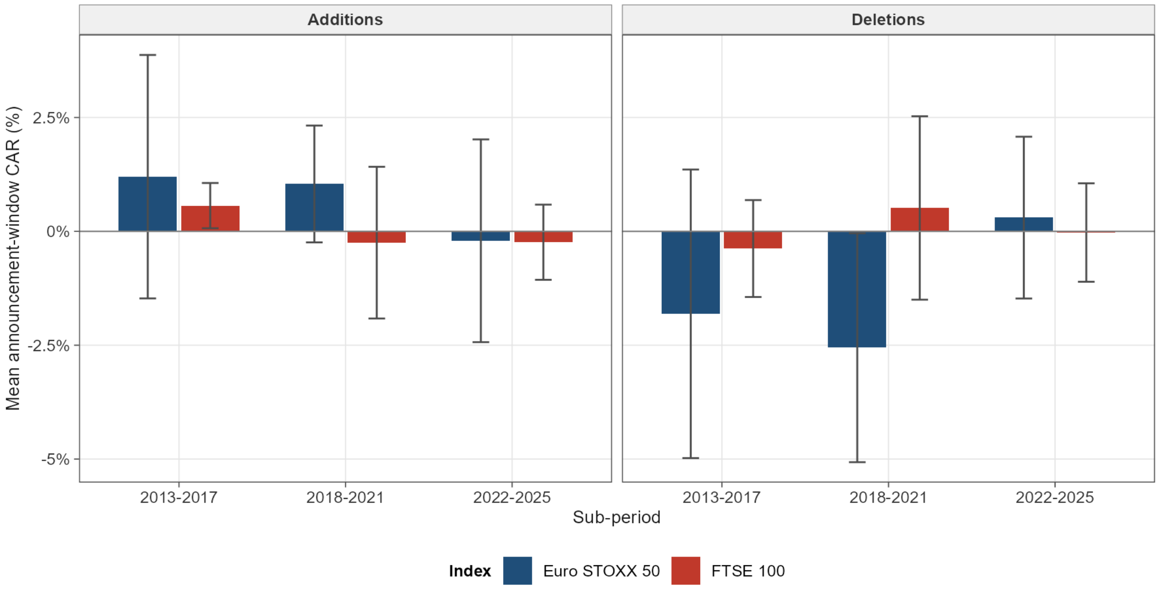
Term	CAR [AD-5,AD+5]	CAR [ED,ED+5]
(Intercept)	-4.364**	-0.221
	(1.870)	*(1.450)*
SSA_max	-2.675*	-0.607
	(1.441)	*(0.568)*
SSA_max:is_late	2.109	1.168
	(1.858)	*(1.032)*
is_late	0.805	-1.035
	(1.637)	*(1.285)*
Size	9.583	48.044
	(72.518)	*(34.610)*
Turn	586.757***	-89.843
	(216.886)	*(146.175)*
WZ_scaled	-0.257	-0.187
	(0.267)	*(0.122)*
Cover	0.364**	-0.063
	(0.182)	*(0.085)*
is_FTSE	-2.463	2.243
	(2.771)	*(1.533)*
N	135	127
R^2	0.209	0.056

Table A5. Index-separate deletion regressions: Table 7 cols (1)-(3) estimated separately for Euro STOXX 50 and FTSE 100. No index fixed effect. HC1 SEs in parentheses.

Term	**STOXX Ann**	**STOXX Eff**	**STOXX Total**	**FTSE Ann**	**FTSE Eff**	**FTSE Total**
(Intercept)	-2.594	-1.483	-1.515	-3.915**	0.951	-4.387
	(1.708)	*(1.621)*	*(3.849)*	*(1.793)*	*(1.223)*	*(2.899)*
SSA_max	0.832	-1.099	-0.878	-0.098	0.417	-0.551
	(1.443)	*(1.780)*	*(4.224)*	*(0.508)*	*(0.489)*	*(0.867)*
Size	13.315	121.619**	256.680	-33.311	-10.803	-40.308
	(59.801)	*(43.892)*	*(158.360)*	*(60.024)*	*(25.598)*	*(85.578)*
Turn	-40.610	-402.656*	-1223.303**	244.735*	-108.935	168.731
	(275.605)	*(225.352)*	*(581.041)*	*(130.803)*	*(123.153)*	*(259.901)*
WZ_scaled	0.382	0.842*	2.027	0.061	-0.309**	-0.312
	(0.493)	*(0.419)*	*(1.268)*	*(0.131)*	*(0.129)*	*(0.292)*
Cover	-0.135	0.021	-0.425	0.211*	0.014	0.404**
	(0.203)	*(0.128)*	*(0.590)*	*(0.122)*	*(0.070)*	*(0.202)*
N	25	25	25	110	110	110
R^2	0.072	0.255	0.212	0.158	0.088	0.115

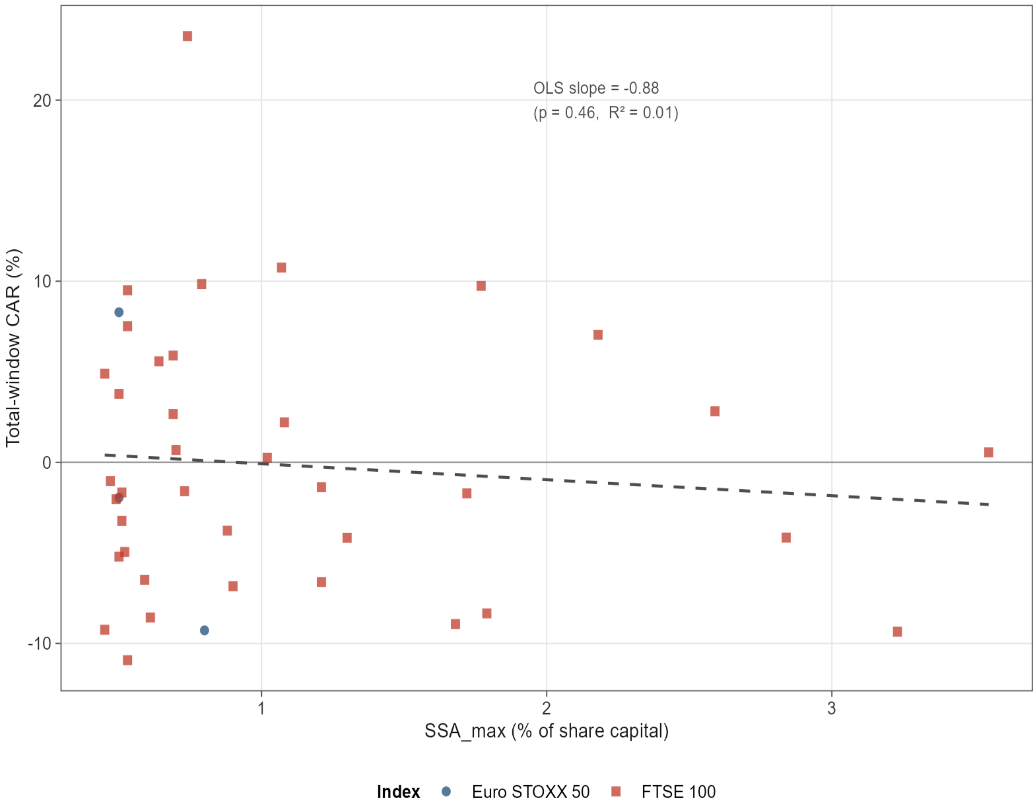
Appendix B: Figures

Figure A1. Mean announcement-window CAR by sub-period. Error bars: +/-1.96 SE.



Error bars: +/-1.96 SE of the mean. Window: [AD-1, AD+1].

Figure A2. Total-window CAR vs SSA_max for addition events (OLS slope = -0.88, p = 0.46). N = 41 additions with at least one disclosed position.



Additions with ≥1 holder above 0.5% EU SSR threshold (N = 41).

Figure A3. Total-window CAR vs SSA_max for deletion events with at least one disclosed position.