The Disappearing Index Effect*

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Abstract

The abnormal return associated with a stock being added to the S&P 500 has fallen from an average of 7.4% in the 1990s to less than 1% over the past decade. This has occurred despite a significant increase in the share of stock market assets linked to the index. A similar pattern has occurred for index deletions, with large negative abnormal returns during the 1990s, but only 0.1% between 2010 and 2020. We investigate the drivers of this surprising phenomenon and discuss implications for market efficiency. Finally, we document a similar decline in the index effect among other families of indices.

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One of the early and persuasive challenges to the efficient markets hypothesis is the observation that stock prices react to investor demand unrelated to fundamentals. Shleifer (1986) and Harris and Gurel (1986) showed that stocks added to the S&P 500 index experienced abnormal returns of approximately 3 percent around the announcement of an index change. Since then, an extensive literature has documented similar price impact in other stock indices such as the Russell and the MSCI, as well as many other settings in which investors buy or sell for reasons unrelated to fundamentals, including mutual fund inflows, mechanical reinvestment of dividends, price pressure around mergers, and Treasury auctions.[1]

The initial studies of S&P 500 changes were performed during a time when index investing was nascent. Shleifer (1986) notes that S&P 500 announcement returns were smaller prior to 1976 than in the 1976-1983 period he focuses on, consistent with more dollars tracking the index leading to more price pressure. Over the past 40 years, driven by inflows into passive mutual funds and ETFs, index tracking has continued to grow at a rapid pace. We estimate that funds tracking the S&P 500 in the form of mutual funds or ETFs have grown from essentially zero in the 1980s to approximately 7 percent of market capitalization in recent years. Other estimates, based on trading volume (Chinco and Sammon 2022) or sell-side research, suggest even higher levels of investor indexation to the S&P 500 today.

What has happened to the price impact associated with being added to or removed from the S&P 500? A natural starting point would be to assume a demand curve with a constant elasticity, hit by a shock that has been growing in magnitude over time:

$$Price\ Impact_{it} = M \times D_{it} \qquad (1)$$

Where $Price\ Impact_{it}$ denotes the percentage change in price, D_{it} refers to the percentage of capitalization of stock i bought upon index addition or sold upon index deletion, and the multiplier M denotes minus 1 over the demand elasticity. Given the rise of indexation, this logic would predict substantially growing price

[1] See e.g., Warther (1995), Mitchell et al. (2005), Ben-Rephael et al. (2010), Lou et al. (2013) and Hartzmark and Solomon (2022).

impact from the 1980s onwards. Conforming to this intuition, we show that the average price impact grew from the 1980s to the 1990s, from an average total return of 3.4% in the 1980s to 7.4% in the 1990s. Surprisingly, however, and consistent with Bennett et al. (2020), we show that the average price impact decreased somewhat in the 2000s to 5.2%, and then fell further to below 1.0% in the most recent decade, statistically indistinguishable from zero, even though indexation has continued to tick upwards. A similar pattern has occurred with index deletions. The average effect of being removed from the S&P 500 was -4.6% in the 1980s, -16.1% in the 1990s, -12.4% from 2000-2009, and -0.6% from 2010-2020. Again, the average return in the past decade is not statistically distinguishable from zero. Taken at face value, this would seem to imply that a multiplier M was declining substantially over the sample.

Why did the S&P 500 index effect seemingly disappear? And if so, can we interpret this change from the lens of market efficiency and a lower multiplier, as an initial look at the data would suggest? We consider four broad classes of explanations:

1) Changing composition of additions and deletions: One possible explanation for the disappearing index effect is that the nature of firms added or dropped from the S&P 500 has changed over our sample. We quickly rule out that the effects we document are driven by changes in the characteristics of additions and deletions since the 1980s, although such shifts do account for *some* of the changes. For example, the size of additions and deletions relative to the total capitalization of the S&P 500 has been shrinking over time. This could partially explain the disappearance of the index inclusion and deletion returns, because empirically, the size of the added or dropped firm is strongly related to the magnitude of the index effect. We use a simple regression-based approach to show that changes in the composition (as measured by Wurgler and Zhuravskaya (2002)'s "arbitrage risk", trading volume, size relative to total index capitalization and coverage by sell-side analysts) account for only a small portion of changes in the average index addition and deletion returns that we have observed over our sample.

2) Migrations: A second class of explanation is that the *net* demand shock D experienced by the typical index addition or deletion is smaller than it appears. We show that in recent years, an increasing percentage of index additions and deletions are "migrations" from the S&P MidCap index. When these stocks are added to

the S&P 500 index, they simultaneously leave the S&P MidCap. In these cases, forced buying by S&P 500-tracking funds is simultaneously matched with forced selling from S&P MidCap-tracking funds, leading to a smaller net demand shock. From the 1990s to the present day, migrations went from about 50% of additions to over 70%. The trend toward more migrations is even stronger among S&P 500 index deletions.

The differences in returns for migrations reflects the increasing importance of the S&P MidCap index over time. In the mid-1990s, migration and non-migration additions had average returns of 10.2% and 6.7%, respectively. By the 2010s, however, direct additions had returns of 5.4%, while migrations had returns of -1.8%. This divergence coincides with the rise of MidCap-focused funds.

3) Front running: A third class of explanation is that index additions and deletions have become more predictable over time, attracting arbitrageurs who front-run index demand. In this explanation, sophisticated market participants who anticipate index changes purchase additions and sell deletions before the announcement day, leading the price to move *before* the official announcement. In the extreme case, in which index changes could be perfectly anticipated, we would expect no abnormal returns at all during the window of time between announcement and when the index change occurs. While we do not have position-level data to measure front-running activity, we can measure pre-event returns, finding mixed evidence to support this hypothesis. In recent years, returns in the three months leading up to the announcement have become somewhat stronger, although the reason for this is subject to interpretation. In addition, a simple rule of selecting the largest eligible firm has become a better indicator of future S&P 500 addition, further suggestive evidence of predictability. That said, predicting which precise stocks get added is still difficult, and we find very little change in the returns experienced in the 20-trading day period before announcement, where one would expect to see higher returns if there were substantial anticipation of index changes. Overall our assessment is that this explanation has played only a limited role in the decline of the index effect.

4) Increased liquidity: The last explanation is that the stock market has simply become more efficient in the context of providing liquidity to S&P 500 index additions and deletions. Or, in the context of Equation (1), that M has declined. We show that even after accounting for the increased migrations changing our estimate of the average demand shock D, M has indeed declined by a factor of approximately 20 for index

additions, and even more so for index deletions. We then evaluate this hypothesis in conjunction with all the other drivers, reaching the same conclusion.

Why has the market for index changes become so much more elastic? Part of the answer is that the stock market is more liquid today than in the past, in the sense that trading costs in other settings have also declined since the 1980s and 1990s. However, this is only part of the story, as trading costs have not fallen by enough between the 1990s and the late 2010s to explain the decline of the index effect. Moreover, the decline in market-wide trading costs predates the disappearance of the index effect.

Several market changes are likely to have facilitated the greater provision of liquidity around index events. First, over the past 15 years, Wall Street trading desks have increased personnel and computing resources devoted to index trading, with several large players (UBS, Goldman Sachs) having specialized sell-side teams. Large passive investors also employ large teams to study and improve liquidity around rebalancing. Second, the distribution of trading volume has become more concentrated around index change events, facilitating liquidity provision (Chinco and Sammon, 2022). Third, despite the large size of the demand shock experienced by additions and deletions, much of it appears to be accommodated by other institutions. Specifically, although index trackers now buy about 7-8% upon index addition, total institutional ownership barely moves around index changes. We interpret this as professional active investors providing liquidity to passive buyers and sellers.

Overall, the findings suggest an account along the following lines. In the 1980s, index changes were unanticipated, index funds were small, and there was mispricing in the market. As index funds grew larger, the mispricing deepened and turned into an opportunity. As a result, the market adjusted to take advantage of this opportunity, in part by better anticipating inclusions, but mostly by creating arrangements where other institutions stood ready to sell to indexers upon inclusions. This worked to eliminate the anomaly on average, despite demand shocks that continued to grow in magnitude over the 2000s and 2010s. In this sense, the decline of the index effect is much like the evidence for other anomalies: they decline once they are well recognized by the market (McLean and Pontiff, 2016).

Our results raise the obvious question of whether the index effect has declined in other settings, such as for the Russell 1000 and other well-tracked indices. Many other papers, including Madhavan (2003) and Petajisto (2011), have shown index addition effects outside of the S&P 500. To this end, we apply our methodology to several other families of indices, specifically the Russell 1000 and 2000, as well as the Nasdaq 100 and other S&P mid- and small-cap indices. Overall, we find similar results for these indices in the sense that addition and deletion returns have declined over the past decade. However, the details and magnitude vary by index, and the statistical and economic significance is generally weaker than the decline we have described for the S&P 500. For the Russell Index additions, the change is not statistically significant. We leave a more complete analysis of these indices to future work.

There is a long and vibrant literature on downward sloping curves and price pressure for individual stocks. Beginning with Shleifer (1986), Harris and Gurel (1986), and Lynch and Mendenhall (1997), dozens of studies analyze the implications of index changes for stock returns.[2] Cai (2007) and Shahrbabaki (2022) distinguish between fundamental news and price pressure. Most closely related to our paper is Bennett et al. (2020), who first noted the decline in the index inclusion effect among additions between 1997 and 2017. Preston and Soe (2021) also document the decline in index inclusion effect among additions and deletions beginning in 1995. Finally, Vijh and Wang (2022) document the lower absolute returns associated with migrations from the S&P MidCap to the S&P 500.

A more recent literature has studied the effects of rising passive ownership, including Qin and Singal (2015), Bond and Garcia (2018), Garleanu and Pedersen (2018), Kacperczyk et. al. (2020), Buss and Sundaresan (2020), Ernst (2020), Malikov (2023), Lee (2021), Coles et. al. (2022). Koijen and Yogo (2019) and Gabaix and Koijen (2022) study implications for inelastic demand curves for stock prices and the aggregate market. Several papers focus specifically on estimating a price elasticity, i.e., how much prices can be expected to move for a demand shock of a given size (e.g., Scholes (1972), Loderer et al. (1991), Bagwell (1992),

[2] For additional evidence on S&P 500 index addition/deletion effects, see e.g., Wurgler and Zhuravskaya (2002), Yang and Morck (2002) and Petaijsto (2011). For evidence on addition/deletion effects in other indices see e.g., Kaul et al. (2000), Madhavan (2003), Greenwood (2005), Chang et al. (2015), Patel and Welch (2017) and Madhavan et. al. (2022).

Kandel et al. (1999) Kaul et al. (2000), Wurgler and Zhuravskaya (2002), Petajisto (2011), Chang et al. (2015)), which we do as well, although there is currently no consensus in the literature.[3]

The paper proceeds as follows. In Section 1, we lay out the puzzle, documenting both the increase in mechanical demand driven by index changes, as well as the puzzling disappearance, on average, of an effect on returns. Section 2 considers, in turn, each of the potential explanations. Section 3 documents the decline of addition and deletion effects in other families of indices. Section 4 concludes.

1. Index tracking and the index inclusion effect 1980-2020

In this section we present the main facts. We first describe how we assemble a list of additions and deletions, before turning to how we identify funds that track the S&P 500. We then present statistics on announcement, effective date, and total returns associated with index changes. Last, we examine whether there is any correlation between net purchases by mutual funds and ETFs tracking the S&P 500 and the returns we observe.

1.1 Data

The S&P 500 index is designed to track the performance of US large market capitalization stocks and be representative of the US economy. To be added, the firm must file 10-K reports and be primarily based in the US. Further, as of 2023, the firm must have a market capitalization of $12.7B or greater, a float-adjusted market capitalization that is at least 50% of this threshold, and an investible weight factor of at least 0.1 i.e., 10% of the shares outstanding must count toward the float. Finally, the firm must meet criteria for minimum float-adjusted liquidity, have the sum of the most recent four consecutive quarters of GAAP earnings be positive, and have positive GAAP earnings in the most recent quarter.[4] At any given point in time, several stocks may meet these inclusion criteria, but a committee inside S&P decides which stock is added to the

[3] For example, Wurgler and Zhuravskaya (2002) highlight that estimates from these papers can range from -3,000 to -1.65. More recent papers including Petajisto (2011) and Chang et. al. (2015) find estimates between -1.5 and -0.84.
[4] For more details, see e.g., Petajisto (2011) and S&P's documentation on their index methodology.

index. According to S&P documentation, "Stocks are added to make the index representative of the U.S. economy and is not related to firm fundamentals (S&P, 2017)."

We obtain data on S&P 500 additions and deletions between 1980 and 2020 from Siblis Research. For each index change, Siblis provides the date the change was announced (announcement date) as well as the date the change was implemented (effective date). If the index changes occur on a weekend or trading holiday, we mark the next trading day in CRSP as the announcement or effective date. We merge these events to CRSP on date and ticker, and hand match cases on names when either (1) there are multiple CRSP permnos associated with that ticker or (2) there are no CRSP permnos associated with that ticker. Using this method, we can match 732 of the 736 additions and 726 of the 731 deletions between Siblis and CRSP for the years 1990 to 2020. Before 1990, Siblis does not provide information on announcement dates, so for the pre-1990 additions and deletions, we use data from Barberis et al. (2005).

For purposes of measuring returns, the full sample we just described is sufficient. But, to have a consistent sample to perform all of our analysis, we remove observations which cannot be matched to the Thompson S12 mutual fund holding data on CUSIP, either the quarter before or the quarter after the index change. We also exclude cases where the firm was either listed, acquired, delisted for reasons other than an acquisition or was an acquirer (i.e., had an ACPERM in CRSP) within 100 days of the index change.[5] These filters exclude e.g., spin-offs, where a security can be added to the index and then quickly removed. Appendix Table A1 describes in more detail the original sample as well as the final sample size after applying all our filters. Appendix Table A2 verifies that our conclusions about absolute addition and deletion returns declining are not sensitive to sample selection criteria.

1.2 Identifying S&P 500 index trackers

[5] We exclude cases where the firm is an acquirer because in the case of a stock merger, there could be significant effects on the number of shares outstanding, which could contaminate our estimates of mechanical buying and selling by S&P 500 index-tracking funds.

To quantify the amount of money tracking the S&P 500 index, we leverage the Thompson S12 data on the quarterly holdings of mutual funds and ETFs. Our goal is to identify funds that tend to buy additions, or sell deletions, around the time of S&P 500 index change. To this end, for each fund, we count the number of times an added stock is not held by the fund the quarter before the addition, but held by that fund the quarter after addition. Similarly, we count the number of times a deleted stock is held by the fund the quarter before the addition, and the stock is not held by that fund the quarter after the addition. We divide the sum of these counts by the total number of additions and deletions each year to compute the fraction of index-tracking trades made by each fund. We classify funds as S&P 500 trackers if, on average across all years that they are present, they perform at least 50% of index-tracking trades each year. According to this methodology, the largest S&P 500 trackers in 2020 were the Vanguard 500 Investor Shares (VFINX) and Admiral Shares (VFIAX), the SPDR S&P 500 ETF Trust (SPY), the Fidelity 500 Index Fund (FXAIX) and the iShares Core S&P 500 ETF (IVV).[6] To allay concerns of overreaching with our classification of S&P 500 funds, in Appendix Figure A1 we show that we obtain a slightly larger estimate for the size of the S&P 500 tracking industry when we identify funds based on their objective codes and names, instead of changes in holdings.

Having identified the S&P 500 tracking funds, we measure net buying and selling by these funds around index changes by adding up the shares held by all trackers the quarter before and after the index change. Then, we define net trading by trackers as: $Net\ Trading_{i,t} = 100\ \times (\Delta Shares\ held_{i,(t+1,t-1)})/ Shares\ outstanding_{i,t+1}$, where both shares held, and change in shares outstanding are split-adjusted using the CRSP cumulative factor to adjust shares outstanding.

Figure 1 shows the average net trading by trackers across additions and deletions each year. Consistent with the aggregate rise of passive ownership, in the early 1990s, net buying by trackers of additions was close

[6] To identify funds based on objective codes we use CRSP objective codes SP and SPSP. To identify funds based on names we follow Appel et. al. (2016) and use variants of "S&P 500", "S and P 500" and "SP 500". We prefer our method of identifying S&P 500 trackers based on changes in holdings to this alternative method because before 1999, the CRSP objective codes (and more broadly, the flag for index funds) are sparsely populated.

to 0% of shares outstanding, while now it is over 6%. This pattern is mirrored for deletions, going from approximately 0% to almost 8% of shares outstanding.

We believe our estimate of net trading by index trackers is a lower bound for several reasons. First, our estimates are based only on S12 data i.e., mutual funds and ETFs. There are surely institutions of other types, such as pension funds and endowments, with assets that directly replicate the index, and which are not included in our calculations. In fact, as argued by Chinco and Sammon (2022), the direct replication industry (i.e., investors who internally replicate indices rather than buy index funds) may be larger than the AUM of explicitly passive funds. Another reason our estimates may be too small is that there are shadow indexers who closely track the S&P 500, but not often enough to be classified as index trackers by our method (Mauboussin et al., 2017). Sell-side research estimates the size of S&P 500 index tracking industry in 2022 to be approximately 13%, about fifty percent higher than our estimate.[7]

1.3. Addition and deletion returns

Figure 2 presents statistics on average returns for S&P 500 index additions and deletions in 10-year rolling windows. Table 1 presents statistics by year. We define the cumulative abnormal return as:

$$CAR_{it} = R_{it} - R_{S\&P\ 500,t} \tag{2}$$

For announcement returns, *R* is measured as the cumulative return between the trading day before the announcement and the trading day after the announcement. Effective date abnormal returns are also defined according to (2) as the cumulative abnormal return between the day before the implementation of the index change and the trading day after the change. For additions, the average period between the announcement and the effective date is 4.8 days; for deletions it is 5.8 days. Our main interest is the CAR_{it}, defined as the cumulative abnormal return from the last trading day before the announcement to the first trading day after

[7] Authors' calculation obtained by dividing predicted net purchases by market capitalization for index additions in the 2022 UBS S&P 500 report. We obtain estimates of a similar magnitude to the UBS estimate when we apply our methodology but use a more generous classification of index trackers. Specifically, if we identify tracking trades as funds increasing the number of shares they hold of index additions, or decreasing the numbers of shares they hold of index deletions, instead of requiring holding no shares before or after the index change.

the implementation. In principle, the CAR_{it} captures the price impact resulting from the market absorbing net demand from index traders. For most of our sample, index changes are pre-announced with much of the return (to the extent that there is a return) occurring on announcement. In the early part of our sample, however, index changes are not pre-announced.

Figure 2 plots the average index inclusion and deletion effect in 10-year rolling windows, while Table 1 reports the year-by-year averages. For additions, the index inclusion effect was 3.4% in the early 1980s, increasing to 7.4% by the 1990s. This is where the effect peaked, as it declined to 5.2% by the 2000s before declining to a statistically insignificant 1.0% in the 2010s. Our results mirror those in Bennett et al. (2020), who show a decline in the index addition effect between 1997 and 2017. We find the deletion effect has followed a similar trend toward zero, albeit in a less smooth way. In the 1980s, firms removed from the S&P 500 had abnormal returns of -4.6%, while in the 90s, they had returns of -16.1%. The deletion effect fell in magnitude to -12.4% in the 2000s and disappeared in the 2010s, with an average abnormal return of -0.6%.

One data point that stands out in Figure 2 is the increase in the inclusion effect in 2020, which drove the uptick in the overall inclusion effect in the late 2010s and 2020. This is due to Tesla being added to the index in November 2020, which, as a fraction of the S&P 500's total market capitalization, was the largest addition of all time (Arnott et al., 2021). Excluding Tesla, the average inclusion effect in 2020 was -3 basis points. In Section 2.1, we examine whether characteristics e.g., a firm's size relative to the total index capitalization can explain cross-sectional and time series variation in the index inclusion effect.

Table 1 also breaks the total index inclusion and deletion effect into the announcement return and the implementation return.[8] The 2nd column shows that, for additions, the announcement return has been declining over time. In the 1980s, it was 3.4%, rising to 4.9% in the 1990s and then falling to 4.1% by the 2000s and to 1.0% by the late 2010s. The 3rd column shows that this pattern is mirrored for effective day

[8] Note that in this table, the announcement return, and implementation return do not necessarily add up to the total return, as there are typically over 6 days between the announcement and implementation i.e., not all these days are included in the t-1 to t+1 window around each event.

returns. Specifically, in the 1980s, the effective date return was around 3.4%, increasing to 3.6% in the 1990s and then declining to 1.4% by the 2000s and close to zero by the 2010s. The 2nd to last row reports the difference in average returns between the 2000-2009 and 2010-2020 periods. Across the total, announcement, and implementation returns, this difference is highly statistically significant.

Columns 5-8 of Table 1 replicate Columns 1-4, but for firms dropped from the S&P 500. Like the results for additions, the implementation and announcement returns became indistinguishable from zero by the 2010s. Also like the additions, this difference is strongly statistically significant.

At this point, the puzzle is clear: returns to index changes grew in the 1990s in a manner that is consistent with the growing importance of index funds, but then declined slightly in the 2000s and disappeared, on average, in the 2010s, despite a growing index fund industry. Another potentially more direct way to illustrate the puzzle is to compare, event-by-event, the return to the size of assets tracking the index. We show this in Figure 3, which plots the index inclusion return against net purchases by index trackers, defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding (multiplied by 100). There is no apparent relationship between net purchases and the index inclusion effect, for either additions or deletions. Specifically, for additions, a regression of inclusion returns on net purchases has a negative slope and an R-squared of 2%, while for deletions the same regression has a negative slope and an R-squared of 6%. Not only has the index effect disappeared, but there does not appear to be a stable relationship between net purchases and returns, as hypothesized by Equation (1).

2. Explanations

In this section we explore four explanations for the declining index effect in the face of increased index tracking.

2.1 Explanation 1: Changing composition of additions and deletions

We have shown that the average returns of S&P 500 additions have been declining over time. A natural first hypothesis is that this trend is driven by a change in the composition of added and deleted firms, rather than a decline in the nature of the index inclusion effect. For example, larger firms typically experience larger inclusion returns, a phenomenon perhaps driven by benchmarked investors being more likely to buy additions that form a large share of the index, as doing so helps them avoid tracking error (this should not apply to index trackers or ETFs, which should aim to track the index perfectly). As a specific application of this, Tesla was the largest ever firm added to the S&P 500 index, relative to the S&P 500's total market capitalization (over 2%). And, as mentioned above, in 2020 Tesla drove a positive overall average addition effect, experiencing a cumulative abnormal announcement return of 5.2% and implementation return of 4.5%.

Another potential change in composition is related to the notion of "arbitrage risk" associated with added and deleted stocks, as discussed by Wurgler and Zhuravskaya (2002). They show that stocks with closer substitutes, and thus lower arbitrage risk, should experience lower price pressure. This is closely related to the idea that price impact should be correlated with fundamental volatility (Kyle, 1985, Chacko et al., 2008). There have been changes in arbitrage risk over time, such as the addition of high-risk internet stocks in the late 1990s.

A third potential change in composition has to do with the amount of investor attention associated with index changes. In the past, index inclusions may have been a large shock to institutional investor attention, leading to increases in sell-side analyst coverage. In more recent years, however, with greater average information production, the effect of index changes on attention may be relatively less important.

To quantify the effect of firm characteristics on the inclusion and deletion effects, we run the following regression separately for additions and deletions:

$$CAR_{it} = b_1 turn_{i,t-1} + b_2\, size_{i,t-1} + b_3 WZ_{i,t-1} + b_4 cover_{i,t-1} + \sum_{k=1}^{4} \gamma_k 1_{era=k} + e_{it} \quad (3)$$

where CAR_{it} is the cumulative abnormal return from the day before the announcement to the day after the implementation. $turn_{i,t-1}$ is the abnormal turnover in stock *i* over the month before the index changes. This is defined as turnover (volume/shares outstanding) minus the value-weighted average turnover across all ordinary common shares (share codes 10 and 11) traded on major exchanges (exchange codes 1, 2 and 3) in CRSP over the same month. $size_{i,t-1}$ is the firm's market capitalization on the last day before the announcement of the index change divided by the total market capitalization of the S&P 500 on the same day. $WZ_{i,t-1}$ is the Wurgler and Zhuravskaya (2002) measure of arbitrage risk, computed as the variance of CAPM regression residuals over the year before the announcement of index addition or deletion. $Cover_{i,t-1}$ is the number of analysts covering the stock in the last earnings announcement before the index change, based on data from IBES. $1_{era=k}$ are dummy variables for 10-year periods e.g., 1980-1989. We demean $turn_{i,t-1}, size_{i,t-1}$, $WZ_{i,t-1}$and $cover_{i,t-1}$. Note that because we include separate dummies for each era, there is no constant term in the regression.

We start by running the regression in Equation 3 without controls for past turnover, size, arbitrage risk, and analyst coverage. This recovers average returns for each of the decades. Results are shown for additions and deletions in Columns 1 and 3, respectively, of Table 2. Note that the averages differ slightly from those shown in Table 1 because we lose a handful of observations where we do not have information on all the characteristics. In the last 3 rows, we compare the coefficients between the various decades.

Column 2 of Table 2 shows the full regression results, including controls. The first quantities of interest are the γ_k i.e., the residual average index inclusion effect not explained by the past intensity of trading volume or relative firm size. For the 1980s, 1990s, 2000s, and 2010s, these coefficients are positive, and statistically significant. The coefficient for the 1990s stays essentially unchanged at 7.4 when including all the firm-level characteristics, suggesting that the index inclusion effect in the 1990s was not entirely explained by these firm-level characteristics. Further, consistent with our previous results, these coefficients shrink from the 1990s to the 2000s, and shrink again from the 2000s to the 2010s. Comparing the difference between e.g., the 1990s and 2010s, we can see that the decline in the index effect is slightly smaller (in absolute terms) once we condition on the changing characteristics (6.6% vs. 5.6%). The difference, however, is still economically large, and statistically significant, suggesting that changing characteristics cannot explain our results.

Next, we turn to the role of the firm characteristics themselves. The logic of including turnover in the regression is that more liquid firms (i.e., firms with more past trading volume) would potentially have relatively smaller index inclusion effects, because the demand shock upon inclusion is a smaller fraction of average past volume. The first row shows that the effect of past turnover for additions has the expected sign i.e., the estimated coefficient is negative, but is statistically insignificant. The second row shows that the size of the firm being added to the index matters, and the magnitude is economically large. Specifically, being 1% larger relative to total index capitalization would imply an 18% larger inclusion effect. Admittedly, an addition of this size is rare, because the average addition is 9 basis points of total index capitalization while the average deletion is 3 basis points of total index capitalization. Further, additions shrank in relative size between 1980 and 2019, going from an average of 12 basis points to 7 basis points of total index capitalization. But our regression estimates imply this would only explain roughly 50 basis points of the decline in the index inclusion effect.

The third characteristic is arbitrage risk, *WZ*, which is related to stock-level volatility. Consistent with theory and Wurgler and Zhuravskaya (2002), *WZ* attracts a positive and significant coefficient. Finally, we find that the effect of analyst coverage is negative and insignificant, suggesting prior sell-side attention is not an important driver of index addition effects.

Column 4 of Table 2 replicates column 2 for S&P 500 index deletions. The coefficients are negative each decade and statistically significant in the 1990s and 2000s. The difference between the 1990s and 2010s is virtually identical once we control for characteristics (14.6% vs. 14.6%), suggesting that changing characteristics of deletions cannot explain the decline in the index removal effect. Turning to the characteristics, turnover surprisingly attracts a negative coefficient, which is not the expected sign, however it is not statistically significant. Size is marginally significant and positive. A possible explanation for this is that large firm deletions are likely to migrate to the S&P MidCap index, which we discuss in the next subsection. Finally, we find that arbitrage risk and analyst coverage have the expected sign, but are insignificant.

The bottom line from Table 2 is that the decline in index effects is not explained by a simple shift in the composition or characteristics of the firms being added or deleted from the index. While not the focus of our paper, composition effects are important for a handful of years, such as the anomalous large average return in 2020 driven by the Tesla inclusion.

2.2 Explanation 2: Index Migrations

A second explanation is that we have mismeasured the *net* demand D (in Eq. 1), and that properly measured demand for additions has fallen, with similar results for deletions. A notable type of index change for which this holds are so-called index "migrations". An index change is a migration when the stock moves from the S&P MidCap index to the S&P 500, or vice versa. An example of this would be Targa Resources, which was dropped from the MidCap and added to the S&P 500 on October 6, 2022. This differs from direct additions, where a firm is added to the S&P 500 from outside the MidCap or SmallCap universe. An example of this is PG&E, which was directly added to the S&P 500 on October 3, 2022.

When a stock migrates from the S&P MidCap to the S&P 500, MidCap-tracking funds sell, and 500-tracking funds buy. Further, over the last 30 years, the passive ownership of mid-cap stocks (i.e., the fraction of these stocks' shares outstanding) has grown dramatically. As mid-cap focused funds have grown, we would expect this to reduce the price impact of a firm being added to the S&P 500. We hypothesize that migrations should have smaller index inclusion effects than direct additions, and that the difference between migrations and non-migrations should be increasing over time.[9]

To quantify differences between migrations and direct additions, we start by obtaining data on S&P MidCap index changes from Siblis Research. Unlike our dataset on S&P 500 index changes, which starts in 1980, the MidCap changes dataset starts in 1995. We follow a similar procedure to the one described in

[9] A similar phenomenon is documented by Burnham et al. (2018) in the context of country reclassifications in the MSCI index.

Section 1.1 to match these observations to CRSP. We define a migration as any stock which is added to (dropped from) the S&P 500 and dropped from (added to) the S&P MidCap within 5 calendar days. Figure 4 shows that migrations have become a steady share of additions and especially deletions. In the 1990s, migrations accounted for about 69% of additions and less than 10% of deletions. In recent years, they both make up over 70% of index changes.

To fully understand the impact of migrations, we need to estimate capital linked to the S&P MidCap index. This is more challenging than identifying funds tracking the S&P 500 because the largest S&P MidCap funds infrequently report their holdings for much of the sample period. Instead, each year, we identify S&P MidCap 400 index funds based on names and correlations. To identify funds based on names, we require that the fund name contains either variants of "S&P", "SPDR" or "S and P" as well as variants of "400" or "MidCap". To identify funds based on correlations, we first restrict to the universe of mid-cap focused equity funds (those with either CRSP objective code "EDCM" or a Lipper objective code that starts with MC) that do not include variants of "Vanguard" or "Russell" in the name. Among these funds, we classify them as S&P MidCap 400 trackers if their returns have a correlation of at least 99.5% with the index itself for three consecutive years. According to this methodology, the largest S&P MidCap trackers in 2020 were the iShares Core S&P Mid-Cap ETF (IJH), the SPDR S&P MidCap 400 ETF (MDY), and the iShares S&P Mid-Cap 400 Growth and Value ETFs (IJK and IJJ).

Figure 5 shows the sum of these funds' AUM, scaled by the total market capitalization of the S&P MidCap 400 index. As can be seen, dollars tracking the MidCap have grown substantially over time, reaching about 6% of capitalization, slightly more than that of the S&P 500, which we showed earlier. All of this suggests that in recent years, stocks that were added to the S&P 500 from the MidCap experienced a significantly smaller net buying pressure than firms directly added to the S&P 500 from outside the S&P 1500 universe.

We now turn to Table 3, which compares the average returns of migrations and direct additions, by decade, for additions and deletions. We find that, in each decade, the returns to migration additions are statistically significantly lower than direct additions, and this gap has been growing over time. Specifically, for direct additions, the index inclusion effect was 10.2% in the late 90s, 8.8% in the 2000s, and 5.4% in the 2010s. The large positive return in the last period is driven by Tesla, which, as previously discussed, had a massive return of 53.35% between its announcement and effective dates.[10] For migrations, the index inclusion effect was 6.7% in the late 1990s and 2.7% in the 2000s . By the 2010s, this effect became negative, at -1.8%. These results are consistent with those in Vijh and Wang (2022), who document smaller absolute returns for migrations between the S&P 500 and the S&P MidCap indices.

Based on the results for migration additions, we would expect that deletions to the MidCap would have returns which become less negative over time. This is true, but the effect is smaller in magnitude than for additions. For direct deletions, the index removal effect was -12.8% in the late 1990s, -15.7% in the 2000s and -6.9% in the 2010s. For deletions which are also migrations, the index removal effect was -17 basis points in the late 1990s, -4.1% in the 2000s, and 6 basis points in the 2010s.

We visualize these trends in Figure 6. The top left panel shows that direct additions to the S&P 500 experienced a decline in the index inclusion effect over the past 25 years. The top right panel shows that, consistent with the increased size of the offsetting demand shock due to the rise of MidCap funds, there has been an even larger decline in the index inclusion effect for migrations. The bottom left panel shows the returns to direct deletions steadily declined in magnitude, while the results in the bottom right panel are noisier for migration deletions.

To sum up, migrations are helpful for understanding some of the decline in the returns associated with index changes, especially for additions. We return to the migrations in section 2.4 where we account for the effect of migrations in assessing the impact for price elasticity.

2.3 Explanation 3: Predictability of Index Changes

[10] Another way that Tesla's addition was unusual is that there was a 32-day gap between the announcement of its addition and the implementation of the index change, while the typical gap is fewer than 10 days. So, the total cumulative abnormal return to Tesla may also be high because other good news about Tesla was released between the announcement date and effective date.

As the amount of money tracking various indices has grown, so has the industry of investors trying to take advantage of the trades they make. For example, there are widespread press reports about Wall Street teams earning large sums betting on index additions and deletions across a variety of indices (see Bloomberg). This behavior is not restricted to proprietary trading desks. In fact, many investment banks (e.g., UBS) publish short-lists of stocks they think will be added to various indices for their wealth-management clients.

If index additions have become more predictable, we should see certain patterns emerge in pre- and post- addition returns. Suppose, to start, that index changes were completely unpredictable. In this case prices should rise around announcement, followed by lower returns over very long horizons. Alternatively, if additions become more predictable, we should see an increase in price before announcement, coupled with reversion in the long run. It is hard to test this scenario, however, because of the endogeneity of index additions. Namely, non-index stocks that increase in value are more likely to be added to the index in the first place.

We start by looking at cumulative abnormal pre-addition returns. To this end, we calculate the cumulative abnormal returns starting 100 trading days before the announcement of the index change to 14 trading days after the announcement. Figure 7 shows that, over the past 30 years, the total price change over this period has been roughly equal (in the 1980s, the total price change was less). The difference, however, is that the price spike on the announcement of the index change has become less sharp over time. Specifically, the cumulative abnormal return up to the day before the announcement was 9.6% in the 1990s, 14.2% in the 2000s and 18.7% in the 2010s. Then, the cumulative abnormal return up to 10 days after the announcement was 17.2% in the 1990s, 17.4% in the 2000s and 19.8% in the 2010s.

As we noted, one issue with Figure 7 is that all of this is defined ex-post i.e., we are looking at the firms that *ended up* getting added. It could be, however, that S&P has become more likely to add firms which went up a lot in the pre-announcement period over time. In short, while the evidence is consistent with higher predictability, it is not dispositive, because one could equally interpret this evidence as saying that S&P 500 has become better at adding the best performing stocks, as we show below.

Table 4 summarizes the pre-announcement returns shown in Figure 7. For each era, and separately for additions and deletions, we show average abnormal returns for the window beginning *nk* days before announcement and ending one day before the announcement, for *n* = 10, 20, 50, and 100. For purposes of discussion, we focus on the shorter windows because they are less confounded by selection, and because front-running activity seems more likely in the immediate window before the event. As can be seen, additions had average [-20,-1] abnormal returns of 1.54% in the 1990s compared to 2.35% in the 2010s. Deletions had average [-20,-1] abnormal returns of -5.56% in the 1990s compared to -3.03% in the 2010s. In the immediate window preceding the event, then, there is no evidence of changes in front running for additions and the evidence goes the other way for deletions. At longer windows, however, the picture is murkier. Additions had average [-100,-1] abnormal returns of 9.6% in the 1990s compared to 18.7% today.

Another way to test whether additions have become more predictable is to see whether, in fact, we can predict which stocks are added to the index. Here we focus on the most salient characteristics of index additions, namely that they are large stocks that are not in the index and develop a simple model of S&P's index inclusion rule. To quantify this, each month, we compute the market capitalization rank of all ordinary common shares traded on major exchanges outside the index.

Then, in Figure 8, we plot the average rank of firms that end up getting added, as well as the 25th and 75th percentile of these ranks.[11] While this is an imperfect ranking system[12], Figure 8 shows that over time, the S&P has moved to picking larger firms, with a smaller interquartile size range. This, however, does not mean that it is easy to predict which particular stocks will be added at any given time, as the average rank of firms added in the last 10 years is around 50. Further, as can be seen, the interquartile range can be quite large, spanning about 40 ranks, suggesting significant randomness in which firms end up getting added.[13]

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[11] In a small subset of years, the mean is above the 75th percentile – these are years where one or two extremely low ranked firms were added to the index.

[12] This ranking system does not account for other index criteria such as (a) the float-adjustment made by S&P (b) the fact that S&P may add non-ordinary common shares and (c) S&P's other rules such as profitability, size, liquidity, and insider ownership.

[13] One concern with the results in Figure 8 is that the number of publicly listed firms has been declining (Doidge et al., 2017). This trend could mechanically increase the rank of added firms if S&P always chose firms in the same part of the

To sum up, the evidence on front-running is mixed. Index changes are more forecastable in the last decade than they were in the past. But we do not observe meaningful changes in returns in the short windows leading up to announcement, leading us to be skeptical that index change predictability is entirely responsible for the patterns that we see. We return to the predictability section in the next section, when we consider it in conjunction with the other explanations.

2.4 Explanation 4: Higher liquidity

A fourth class of explanation is that the market is more efficient today at accommodating the required changes in ownership associated with index additions and deletions. Or, in the context of Equation 1, that the multiplier *M* on demand shocks has declined.

2.4.1 Preliminary estimates

To estimate how much *M* has changed, we take means of Equation 1 by decade, and rewrite it to reflect the fact that the average net demand shock *D* varies for index migrations compared to non-migrations:

$$\overline{CAR} = M \times \overline{D} = M \times (w \cdot \overline{D}_{Migrations} + (1 - w) \cdot \overline{D}_{NonMigrations}) \qquad (4)$$

Our goal is to estimate how much *M* has declined. This exercise is only possible beginning in 1995, when we have information on index migrations. The top 6 rows of Table 5 show these results, separately for index additions and deletions. For example, in the 2010-2020 period, the average abnormal return for 153 additions was 0.80%. 63% of additions were migrations with an average net demand shock of 0.3% of market cap; the remaining 37% of additions experienced a net average demand shock of 5.6%. This yields an estimate of *M* of 0.37, or equivalently, a demand elasticity of -2.72. Repeating this exercise era by era, the multiplier *M* has fallen by a factor of roughly 20, from 6.75 in the late 1990s to 0.37 in the last decade. A similar pattern

firm-size distribution. To address this concern we replicated the results in Figure 8 but used the percentile rank of added firms instead of the numerical rank. We found a similar time-series trend to that in Figure 8, suggesting that the decline in the universe of public firms does not explain this result.

appears for index deletions, with *M* falling from 10.76 in the late 1990s to 0.7 in the last decade. In summary, even after accounting for the impact of index migrations, liquidity has increased substantially.

As we noted, our estimate of the multiplier can be converted into an elasticity by taking $-1/M$. We can benchmark this against the large range of different price elasticity estimates from the literature on index changes. For example, Wurgler and Zhuravskaya (2002) provide a summary table of these estimates, which range from -1 (Shleifer, 1986) to -37.2. (Kandel et al., 1999). Our estimate is -0.15 to -0.09 in the 1990s, -0.28 to -0.17 in the 2000s and -2.72 to -1.44 in the 2010s.

One reason that our calculations of price elasticity are smaller in magnitude than previous estimates in the literature (i.e., for a given demand shock, we find higher price impact) is because our estimates for the demand shock are smaller in magnitude. For example, Petajisto (2011) assumes a 10% demand shock, which is larger than the average demand shock we measure at the end of our sample.[14]

In Table 6, our primary estimates of the multiplier *M* are based on the event return, computed throughout the paper as the abnormal return beginning a day before the announcement of an index change and ending the day after implementation. In doing so, it leaves out changes in the index effect that might be driven by higher predictability. For this reason, the bottom 6 rows of Table 6 also provide estimates of *M* based on a longer horizon return, computed as the cumulative abnormal return of each addition/deletion, beginning 20 days before the announcement and ending one day after implementation. Here, the results are similar, albeit slightly smaller, with *M* falling by a factor of roughly 7 for additions and deletions between the 1990s and 2010s. In other words, even if we allow for increased predictability of index changes to play a role, we cannot escape the conclusion that the multiplier has changed.

2.4.2 Estimates using controls

[14] Another paper that computes elasticities from index changes is Chang, et. al. (2014), who obtain an elasticity of -1.5, relying on estimates of index linked assets provided by Russell. We believe it is important to focus on index trackers rather than all benchmarked investors, because only index trackers appear to buy additions and sell deletions near the change date. We have investigated this issue and provide a fuller discussion in the Internet Appendix.

Our estimates above suggest that M has fallen over time. We now show that we reach the same conclusion, even after controlling for the other drivers of returns that we have discussed earlier in the paper. To do so, we present regressions of the form:

$$CAR_{it} = b_1 turn_{i,t-1} + b_2\, size_{i,t-1} + b_3 WZ_{i,t-1} + b_4 cover_{i,t-1} + \sum_{k=1}^{3} \gamma_k 1_{era=k} \times D_{era=k} + e_{it} \tag{6}$$

where $D_{era=k}$ is an estimate of the average *net* demand shock each decade. As in Equation 3, we demean $turn_{i,t-1}$, $size_{i,t-1}$, $WZ_{i,t-1}$ and $cover_{i,t-1}$. D denotes the average size of the demand shock for that decade, just as we had in Table 5, taking into account the blend of index migrations and non-migrations. In this specification, the slope coefficients γ_1, γ_2 and γ_3 can be interpreted as the multiplier M for that decade of additions or deletions, after controlling for the other drivers of differences in returns.

These results are presented in Table 6. We follow a parallel structure to Table 5 and present estimates based on both the cumulative abnormal return from the day before the announcement to the day after the implementation, as a well from 20 days before the announcement to the day after the implementation. The estimates in column 1 mirror those in Table 5, with a decline of the multiplier from 6.8 to 0.3 (the differences are due to a slightly smaller sample that we can match to the characteristic variables). Column 2 shows that adding controls for characteristics shrinks the decline of the multiplier, but it is still significant, going from 6.6 to 0.7.

In column 3, we instead swap the left-hand side variable to a longer-window return that starts 20 days before the announcement, rather than a day before the announcement. Here, we see the level of the multiplier is higher, but it also decreased significantly from 9.1 to 1.3 between the 1990s and the 2010s. In column 4, we again add all our characteristics, and find that the decline of the multiplier M is still significant, going from 8.7 to 1.7. Columns (5)-(8) mirror the analysis from columns 1-4, except they use deletions instead of additions. Again, we find that the decline in the multiplier is robust to both controlling for characteristics and including a larger pre-event return, to account for increased predictability.[15]

2.4.3 Why did the market become more efficient at accommodating index changes?

Our analysis in 2.4.1 and 2.4.2 suggests that, even after controlling for all the potential drivers of the index effect (characteristics, migrations, and predictability), the market has become significantly more efficient in accommodating index changes. How and why did this happen? While this exercise is more speculative, below we explore some of the potential forces associated with these changes, including: (1) overall increases in market liquidity and reductions in trading costs in other settings (2) coordination of trading around index changes, and (3) accommodation of index changes by active managers (4) accommodation by firms issuing stock. We find evidence for all but the last.

Increases in overall market liquidity

The US stock market has become more liquid overall since the 1980s and 1990s, in the sense that it has gotten cheaper to trade without moving the price. We consider two ways of measuring trading costs. Amihud and Mendelson (1986) suggest the bid ask spread as a simple measure of trading costs. To quantify this, we use the WRDS intraday indicators suite to obtain measures of the bid-ask spread based on high frequency data. This dataset uses the method in Holden and Jacobsen (2014) to compute the percent effective spread. The percent effective spread is the percent distance away from the midpoint that the (value-weighted) average trade occurs at each day. Given that our study spans 1980-2020, we need to leverage both the second-based version of TAQ, which runs from 1993-2014, and the millisecond-based version of TAQ, which runs from 2003-present. We do not have a good measure of trading costs before 1993.

[15] We have experimented with several versions of Table 7, including allowing for a separate estimate of M for migrations and non-migrations, as well as allowing the effect of the control variables to vary by decade. See the Internet Appendix for additional details.

The red line in Figure 9 plots the value-weighted average effective spread for all ordinary common shares traded on major exchanges, computed using TAQ data. Value-weighted average effective spreads have experienced a large time-series decline, from 60bp to 6bp. The decline is similar when examining an equal-weighted average of the smallest 100 stocks by market capitalization in the S&P 500. Note that the timing of the increase in overall market liquidity (which is most pronounced in the 1995-1998 and 2002-2005 periods) does not closely match the pattern of changes we observe in the index effect. In other words, while the changes in the index effect are occurring over a period of enhanced overall liquidity, this is not the whole story.

The bid-ask spread captures costs associated with small trades near the midpoint. But the type of trades executed on days of index changes likely don't fit this description: the fraction of shares that need to be purchased by index funds are enormous, now making up over 7% of total shares outstanding. For this reason, we also examine implementation shortfall collected from Virtu Financial. The implementation shortfall is the difference between the arrival price and the execution price for a trade. The implementation shortfall, plotted as a blue line in Figure 9, fell significantly less than the average bid-ask spread over our sample.

Coordination and specialization of trading

Over the past 15 years, Wall Street trading desks have increased personnel and computing resources devoted to index trading. Large players, including UBS and Goldman Sachs have specialized sell-side teams. Passive fund managers also employ large teams to study and improve liquidity around rebalancing. We have confirmed this in discussions with several large index investors, including Blackrock, which alone employs a team of over 60 people in index research.

Further, trading around index changes has become increasingly concentrated (Chinco and Sammon, 2022). We interpret this using the logic of Admati and Pfleiderer (1988): to coordinate on this "sunspot", index providers have moved to a system of disclosing ahead of time which stocks they are going to trade and when (Li, 2021).

Accommodation by other institutions

Liquidity around index changes has increased, but who provides it? Below we show that liquidity is provided, on average, by other institutions exiting their positions, rather than accommodation by other parties such as retail investors. In other words, while a large, dedicated group of mutual funds and ETFs *must* buy, on average, *total* institutional ownership changes very little around these events. To quantify this, we obtain data on institutional ownership from Thompson 13F. Specifically, we examine changes in 13F ownership from the quarter before to the quarter after the index change. These changes are tabulated in Table 7, which compares the changes in ownership by S&P 500 trackers to the total change in institutional ownership. Despite the rise in the change in tracker ownership, there has been (if anything) a decline in the change in 13F ownership. For example, the table shows that for the average addition in 2020, index trackers buy 7.53% of shares outstanding. However, institutional ownership only increases by 0.65% of shares outstanding. This suggests that other institutions have stepped up to meet the buying and selling pressure from S&P 500 funds. The same pattern appears for deletions: in 2020, index trackers sell an average of 8.45% of shares outstanding upon deletion, but institutional ownership overall falls by only 1.42%.

We also examine the net trading behavior of active and passive mutual funds and ETFs around S&P 500 index additions and deletions. We identify passive funds in the S12 data using the methodology in Appel et. al. (2016) and define active funds as all remaining funds. The "Passive" column of Table 7 shows that, on average, passive funds buy a smaller percentage of additions' shares outstanding than S&P 500 trackers. This is consistent with some additions being migrations, where MidCap-tracking passive funds sell shares to S&P 500-tracking funds. The "Active" column shows that active mutual funds are not the group providing liquidity, as their average net demand is roughly zero. This implies that non-S12 filing institutions (e.g., hedge funds, pension fund, endowments) are the primary liquidity providers around addition events.

Accommodation by corporate share issuance?

A last hypothesis is that index additions are partially accommodated by firms that issue shares into the rebalance. A few high-profile examples of this, such as CoStar upon its addition to the S&P 500 in 2018, where it concurrently issued $750 million of new equity, suggest the possibility of this phenomenon being important. We have investigated changes in split-adjusted shares outstanding around all S&P 500 index additions and deletions beginning in 1980. The fraction of firms that have issued stock near S&P 500 membership changes increased somewhat in the 2000s, but then declined in the 2010s. Large stock issuances around index changes are rare. Corporate issuance is not a major force driving the improvement in liquidity around index rebalances.

3. Discussion and extension to other indices

Our findings suggest the following sequence of events. In the 1980s, index changes were unanticipated, but index funds were small, so addition and deletions effects were relatively modest. As index tracking grew larger throughout the 1990s, the mispricing deepened and turned into an opportunity. As a result, the market adjusted to take advantage of this opportunity, in part by better anticipating inclusions, and in part by creating arrangements where other institutions stood ready to sell to indexers upon inclusion. At the same time, the S&P 500 grew to rely more on index migrations (especially for deletions), which helped to reduce overall price impact, and benefitted from increasing assets tracking midcap indices. Together, these forces worked to eliminate the index addition and deletion anomalies on average, despite demand shocks that continued to grow in magnitude over the 2000s and 2010s.

Our interpretation raises the question: do we observe similar reductions in addition and deletion returns associated with other indices, such as the Russell 2000, or the Nasdaq 100? A complete analysis of this question would have to acknowledge the myriad of differences between these indices, including how index changes are announced, how predictable they are, and estimates of how much capital has tracked these indices over time. Still, it is useful to understand whether the broad patterns we have described for the S&P 500 – and, as originally highlighted by Bennett et al. (2020) – exist in other settings.

Below we expand our event return analysis to several other families of indices, choosing to focus on indices for which we can track changes for a 20-year or more period. To preview our results, we show that, like our findings for the S&P 500, such effects grew from the 1990s to the 2000s, and diminished thereafter for the Russell 1000 and 2000, as well as the S&P MidCap, SmallCap and Nasdaq 100. We would like to emphasize, however, that there are differences in magnitudes across the different indices and few of these differences are individually statistically significant.

3.1 Russell indices

Each May, Russell ranks firms according to their float-adjusted market capitalization ahead of their annual index reconstitution, which typically occurs on the fourth Friday of June. Before 2007, the 1000 largest firms would comprise the Russell 1000, while the next 2000 largest firms would make up the Russell 2000. After 2007, Russell switched to a banding rule, where a firm needed to be more than 2.5% of the total Russell 3000E's capitalization away from the 1000th ranked stock to switch indices (see e.g., Coles et al. (2022) for more details).

For the Russell 1000 and 2000, there are six types of index changes to consider: (1) firms that switch from the Russell 1000 to the Russell 2000 (2) firms that switch from the Russell 2000 to the Russell 1000 (3) additions to the Russell 2000 from outside the Russell 3000 universe and (4) additions to the Russell 1000 from outside the Russell 3000 universe (5) deletions from the Russell 2000 to outside the Russell 3000 universe and (6) deletions from the Russell 1000 to outside the Russell 3000 universe. We focus on additions to the Russell 1000 and 2000 from outside the Russell 3000 universe, as these are most comparable to direct additions to the S&P 500. We do not consider deletions from the Russell 3000 to outside the Russell 3000 universe, as these are often firms that are delisting and therefore do not pass our sample selection criteria.

We obtain data on Russell index membership from 1990 to 2020 directly from FTSE Russell. To quantify index addition effects, we apply the same methodology we used for S&P 500 index changes with the following minor change. Rather than use the cumulative abnormal return from the day before the announcement date to the day after the effective date, we instead use the cumulative market-adjusted return from the day before the ranking date in May to the day after the implementation, typically in June (Madhavan, 2003). The market adjusted return is defined as the return on the stock minus the return on the CRSP value weighted index over the same period. As with the S&P 500, we exclude firms that were either listed, acquired, delisted for reasons other than an acquisition and firms which were acquirers (i.e., had an ACPERM in CRSP) within 100 days of the index change.

In Table 8, we show that, consistent with Madhvan (2003) and Petajisto (2011), there were positive returns associated with direct additions to the Russell 1000 and 2000 indices in the 1990s and large returns associated with these index changes in the 2000s.[16] Mirroring our results for the S&P 500, these effects grew from the 1990s to the 2000s. This increase may have been driven by an increase in the demand shock associated with index addition, as IWB and IWM, the largest Russell 1000 and 2000 ETFs, were launched in May 2000. In terms of magnitudes, for stocks added to the 2000, addition cumulative market-adjusted returns increase from an average of 2.2% in the 1990s, to 8.3% in the 2000s and thereafter declined to 3.1% in the 2010s. For stocks added to the 1000, the effect increased from 1% in the 1990s, increasing to 17.0% in the 2000s and then decreasing to 8.53% in the 2010s. As the bottom rows of the Table show, however, none of these individual declines between the 2000s and 2010s are statistically significant.

Unlike changes to the S&P 500, changes to the Russell indices are based on mechanical rules and may therefore be easier to predict. This makes the similarity between the time-series trends for the Russell 1000 and 2000 indices and S&P 500 striking, as changes in predictability are not likely the drivers of a weaker Russell index inclusion effect in recent years. Other factors, such as increased event-specific liquidity arising from pre-arranged trades, may be more important in explaining the smaller returns to Russell index additions in the 2010s relative to the 2000s.

3.2 S&P SmallCap and MidCap

The broader S&P 1500 universe includes all firms in the S&P 500, the S&P MidCap 400 and the S&P SmallCap 600. These indices are not as widely tracked as the S&P 500, but still attract considerable attention and have mutual funds and ETFs that track them. The same rules of profitability and liquidity for the S&P 500 also apply to their other indices, with the main difference being the size threshold for index inclusion.

[16] We would like to highlight, however, that the large returns in the 2000s are largely driven by the year 2000 itself, where both direct additions to the Russell 1000 and 2000 had returns greater than 30% on average.

For the MidCap, there are six types of index changes: (1) additions from outside the S&P universe (2) deletions to outside the S&P universe (3) additions from the S&P 500 (4) deletions to the S&P 500 (5) additions from the SmallCap (6) deletions to the SmallCap. For the SmallCap, there are also 6 types of index changes: (1) additions from outside the S&P universe (2) deletions to outside the S&P universe (3) additions from the S&P 500 (4) deletions to the S&P 500 (5) additions from the MidCap (6) deletions to the MidCap. As with the Russell family of indices, we focus on direct additions to the MidCap and SmallCap from outside the S&P 1500, as well as direct deletions to outside the S&P 1500 universe.

We obtain data on MidCap changes between 1995 and 2020 and SmallCap changes from 1997 to 2020 from Siblis Research. We apply an almost identical methodology for computing index inclusion and deletion effects, with one minor change: Siblis does not provide announcement dates for the MidCap and SmallCap, so we use a window from 10 days before to one day after the index change, as changes are typically announced 5 business days in advance. As with the S&P 500, we drop firms that were either listed, acquired, delisted for reasons other than an acquisition and firms which were acquirers (i.e., had an ACPERM in CRSP) within 100 days of the index change. Finally, for consistency across benchmarks, and as with the Russell index changes, we use cumulative market-adjusted returns.

Table 8 shows that addition effects for the MidCap increased from the 1990s to the 2000s, and decreased thereafter, going from 5.6% in the 1990s, to 8.3% in the 2000s and 5.7% in the 2010s. Similarly, deletion effects grew and then shrunk from -4.5% in the 1990s, to -18.3% in the 2000s and -1.2% in the 2010s. The effect of being added to the SmallCap hasn't changed much over the past 30 years, consistently hovering around 6%, but the effect of being deleted from the SmallCap increased and then shrunk, from -6.7% in the 1990s to -24.6% in the 2000s and finally -12.2% in the 2010s. As with the changes to the Russell indices, except for the increase in deletion returns for the S&P SmallCap index, none of the changes between the 2000s and 2010s were statistically significant.

3.3 Nasdaq 100

The Nasdaq 100 comprises the 100 largest non-financial companies with a primary listing on the Nasdaq exchange, with a few exceptions as stipulated by index rules. We obtain data on Nasdaq 100 index changes between 1995 and 2020 from Siblis Research. As with the S&P 500, we drop firms that were either listed, acquired, or delisted for reasons other than an acquisition and firms which were acquirers (i.e., had an ACPERM in CRSP) within 100 days of the index change. Again, as with the MidCap and SmallCap, we do not have announcement dates for the Nasdaq 100, but these changes are typically announced 5 business days in advance, so we use a window of 10 days before the change to one day after when computing index addition and deletion effects. Finally, as we describe above, we focus on market-adjusted returns for our sample of Nasdaq index changes.

Table 8 shows that there has been a steady decline in the effect of being added to the Nasdaq 100, going from 3.9% in the 1990s to 2.6% in the 2000s and 2.0% in the 2010s. The deletion effects are consistently minimal, hovering near zero for the past 30 years. And once again, none of these declines from the 2000s to the 2010s are statistically significant.

3.4 Summary

Overall, the results for the Russell 1000 and 2000, S&P MidCap and SmallCap, and Nasdaq 100 paint a picture consistent with our main results: index addition and deletion effects grew into the 2000s and shrunk thereafter, but the statistical significance is weak. As a final test, in Column 9 of Table 8, we pool together all the additions from the Russell 1000, Russell 2000, S&P MidCap, S&P SmallCap and the Nasdaq 100. These results mirror the patterns documented in the individual indices, showing a decline of 4.2% in addition effects across all indices, significant at the 5% level. Finally, in Column 10 of Table 8, we pool together all the deletions from the S&P MidCap, S&P SmallCap and the Nasdaq 100. Here, the deletion effect shrinks by an average of 10.3 percent points between the 2000s and 2010s, statistically significant at the 1% level.

4. Conclusion

According to efficient markets theory, if a class of investors were to buy or sell a stock for reasons unrelated to fundamentals, well-capitalized arbitrageurs should respond aggressively to provide liquidity, limiting the price impact. The well-known index effect, whereby a stock added to an index such as the S&P 500 goes up in price, is often held up as an example of market inefficiency. The notion of a downward sloping demand curve is a key ingredient in most behavioral finance models of the stock market.

Over the past decade, the well-known index effect for the S&P 500 has disappeared, with the average addition or deletion experiencing abnormal returns near zero. In this paper, we consider four explanations for why this happened. To sum up, our assessment is that the declining index effect is driven primarily by two factors: in the role of migrations from the S&P MidCap Index, as well as an overall increase in the market's ability to provide liquidity to index changes. A third factor, increased predictability of index changes, also plays a small role. Our overall conclusion is that, when demand shocks become regular and repeated, competitive markets adapt over time to minimize price impact, in the spirit of Lo's (2004) adaptive markets hypothesis.

While our findings uncover and quantify the forces driving the decline of the index effect, they leave open another puzzle. Namely, S&P 500 index changes have been around since 1957, but it took until the 2010s for the market to evolve to provide meaningful liquidity around index changes and neutralize the price impact. Why did it take so long? And why did it take much longer for the market to adapt than in the context of other anomalies related to informational efficiency? We expect subsequent work to explore these questions.

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Figure 1. Net buying and selling by S&P 500 index trackers, by year.

Net buying and selling are defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding (multiplied by 100). Each point represents an equal-weighted average among events, by year. The red line represents a LOWESS filter with bandwidth equal to 0.8.

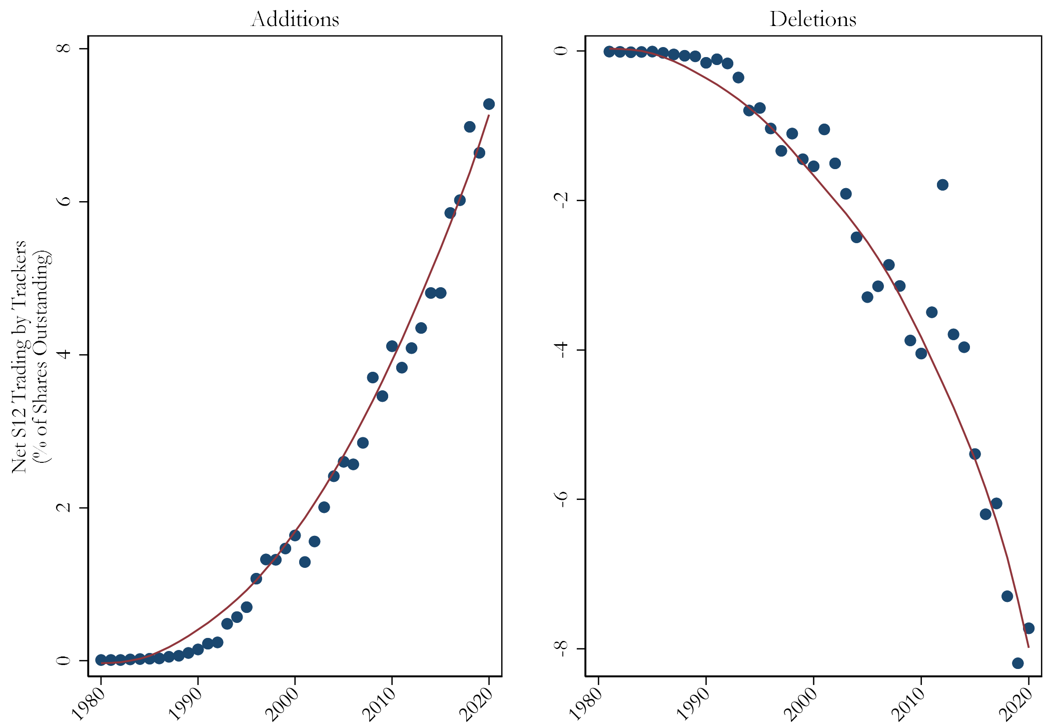


Figure 2. Average index effect by year.

For each event, we compute the cumulative abnormal return over the period of interest. Lines represent 10-year moving averages of the yearly averages.

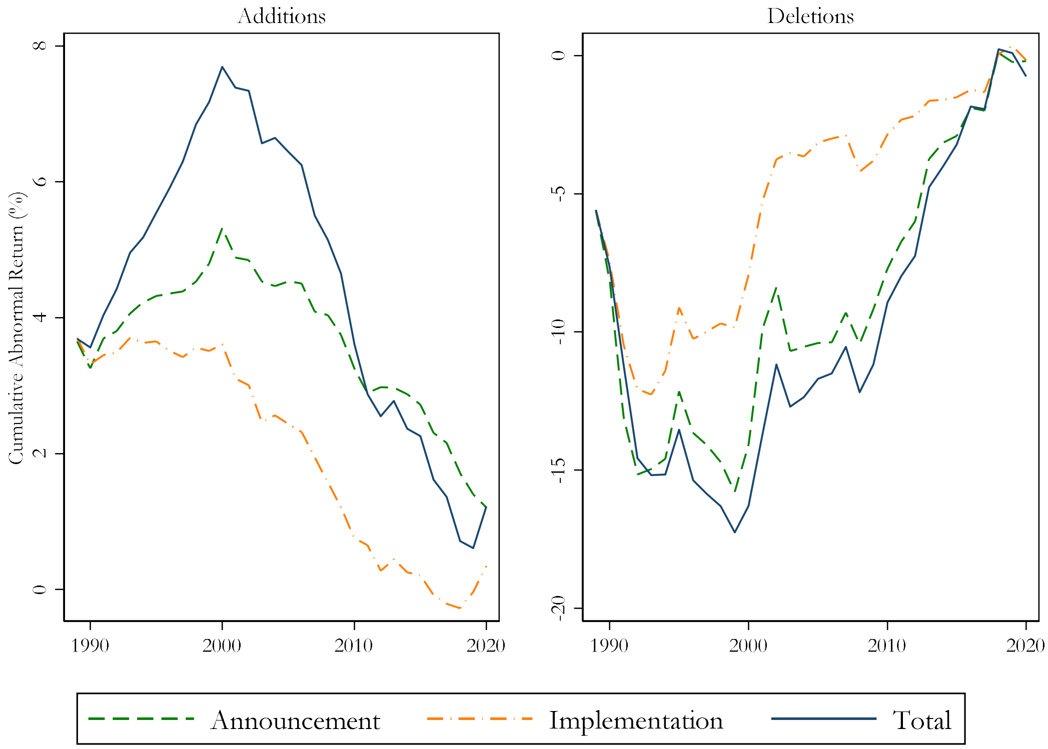


Figure 3. Net purchases and the index effect.

Each point represents an individual addition or deletion event. Net purchases are defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding (multiplied by 100). The vertical axis represents the total inclusion effect return i.e., the abnormal return from the day before the announcement to the day after the implementation.

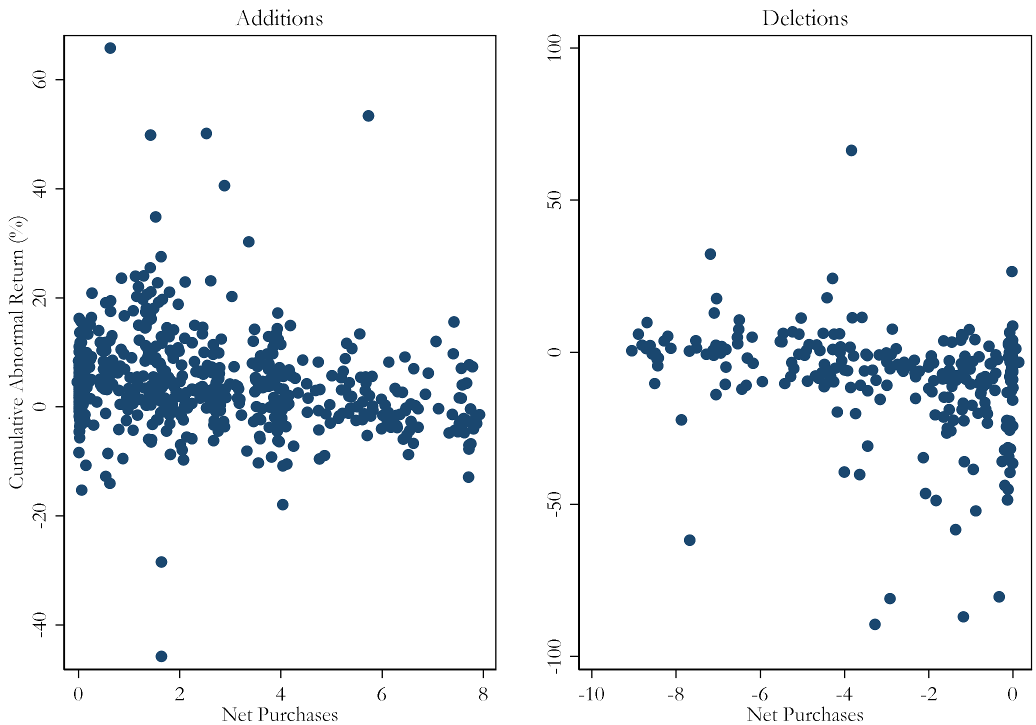


Figure 4. Migrations as a fraction of S&P 500 additions and deletions.

Each year, we define migration additions as firms which are simultaneously added to the S&P 500 and dropped from the S&P MidCap. Migration deletions are firms that are simultaneously dropped from the S&P 500 and added to the S&P MidCap. Then, we compute the share of all additions and deletions in our sample that are classified as migrations, respectively. Lines represent 10-year moving averages.

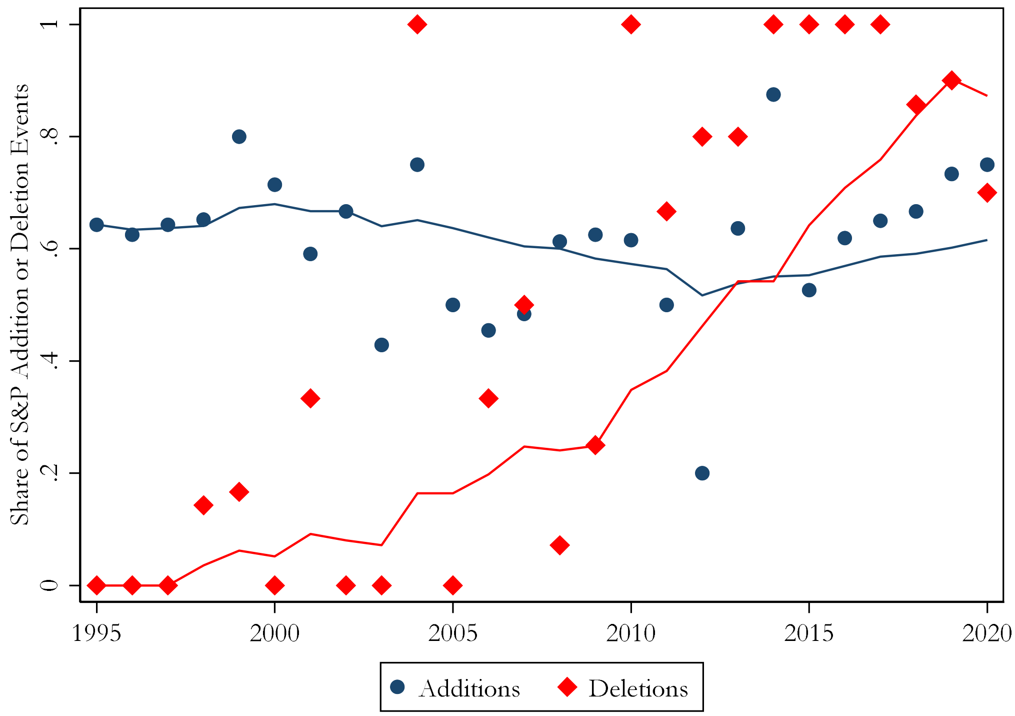


Figure 5. Percent of S&P MidCap 400 owned by index trackers.

Each year, we identify S&P MidCap 400 index funds based on names and correlations. To identify funds based on names we require that the fund name contain either variants of "S&P", "SPDR" or "S and P" as well as variants of "400" or "MidCap". To identify funds based on correlations, we first restrict to the universe of mid-cap focused equity funds (those with either CRSP objective code "EDCM" or a Lipper objective code that starts with MC) that do not include variants of "Vanguard" or "Russell" in the name. Among these funds, we classify them as S&P MidCap 400 trackers if their returns have a correlation of at least 99.5% with the index itself for three years in a row. Finally, we add up the total assets of these funds, and divide them by the total market capitalization of the S&P MidCap 400 index. Line represents a 10-year moving average.

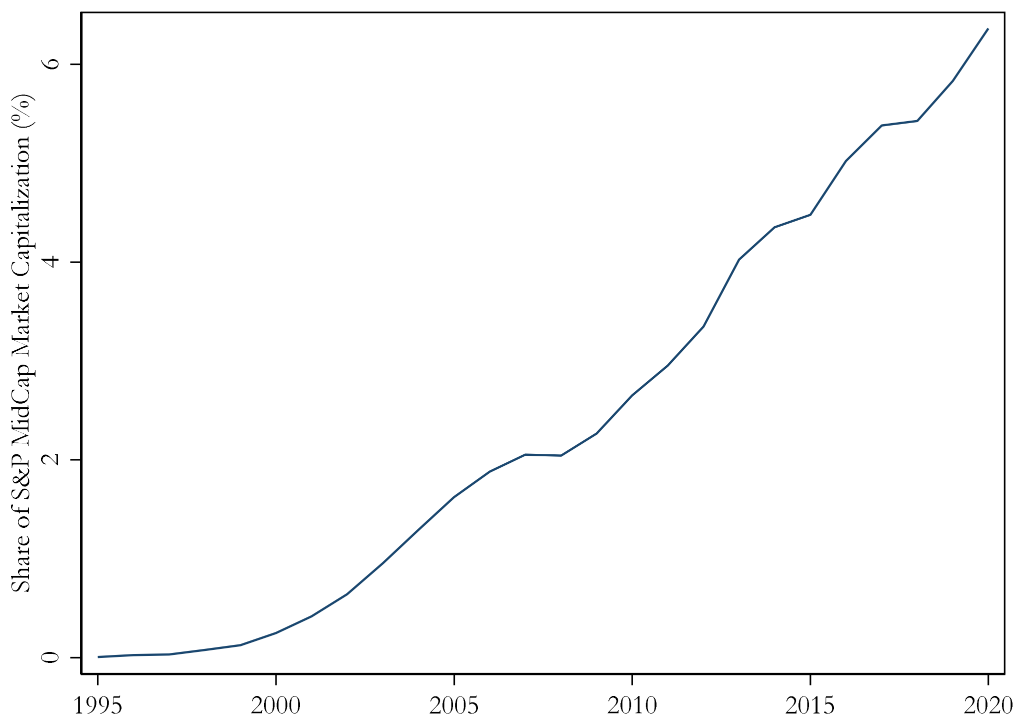


Figure 6. Comparing addition and deletion returns across index migrations and "direct additions" or "direct deletions"

For each event, we compute the abnormal return from the day before the announcement to the day after the implementation. Blue dots represent the average abnormal return each year. The red lines represent 10-year moving averages.

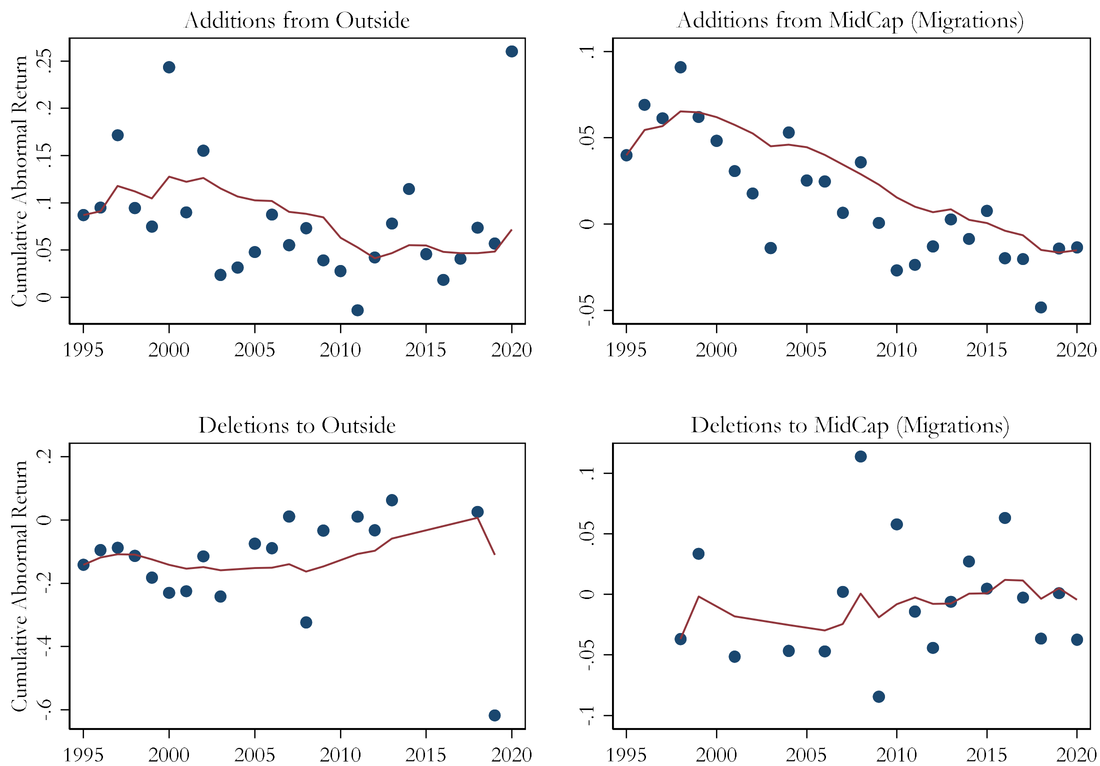
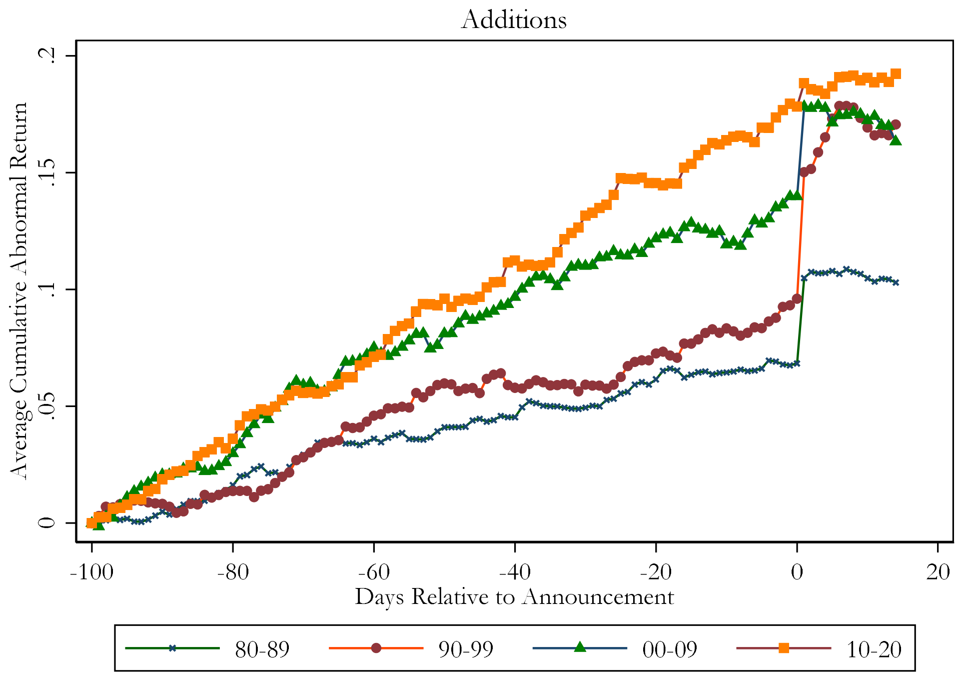


Figure 7. Cumulative abnormal pre-addition and pre-deletion market-adjusted returns.

Average cumulative abnormal returns in event time, pooled for 1980-1989, 1990-1999, 2000-2009, and 2010-2020. Event time of zero denotes the announcement date. Returns are normalized to start at zero, 100-trading days before the announcement.



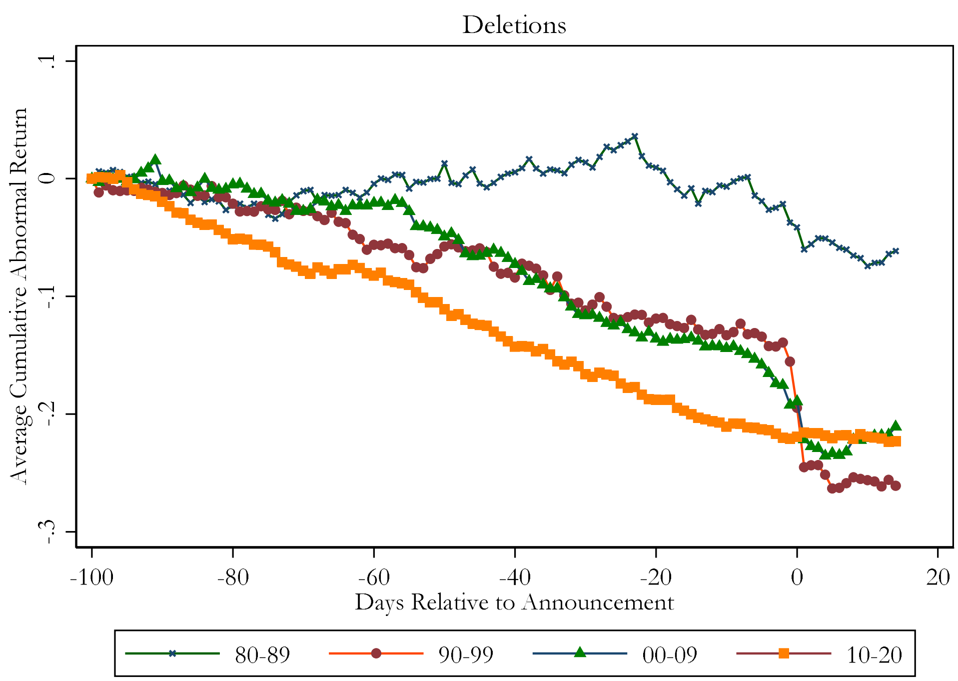


Figure 8. Rank of additions among stocks outside the S&P 500 index by year.

Each month, we rank all ordinary common shares traded on major exchanges outside the S&P 500 by market capitalization. Then, each year, we plot the average rank, as well as the 25th percentile and 75th percentile ranks of stocks which ended up being added the month before their index addition.

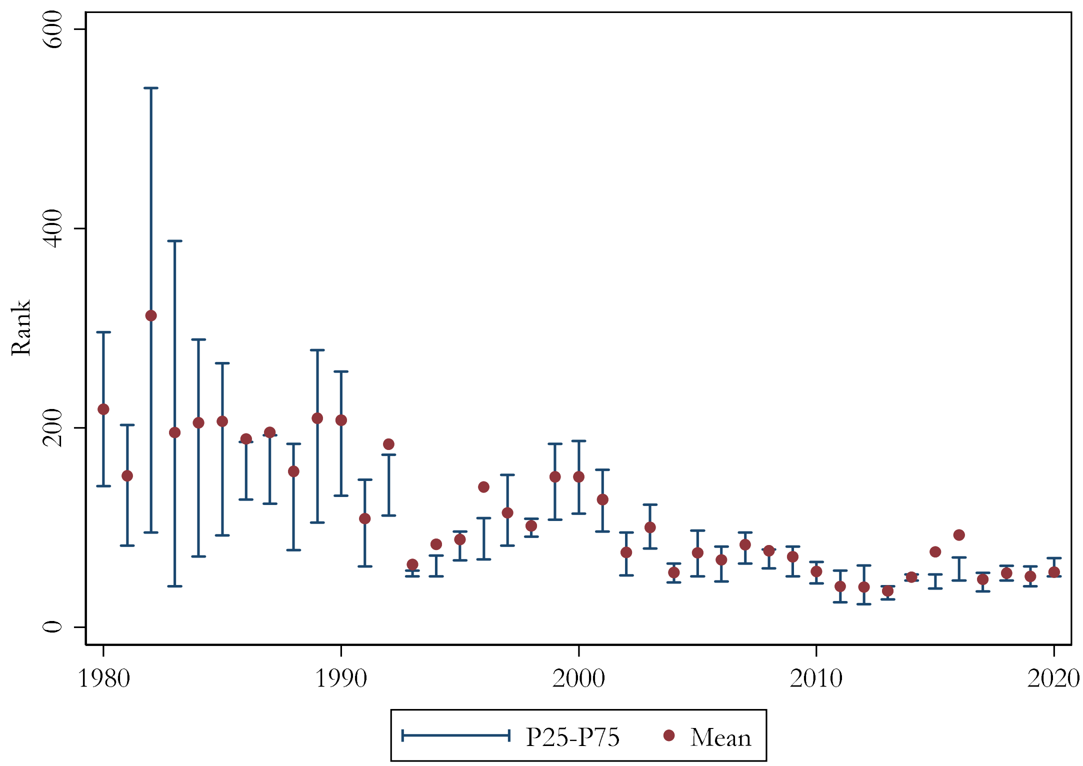


Figure 9. Value-weighted average effective bid-ask spreads and implementation shortfall.

Percentage effective spread is computed using TAQ data with the method in Holden and Jacobson (2014). The red line plots the value-weighted percentage effective spread among all ordinary common shares traded on major exchanges i.e., the weights are proportional to each firm's one-month lagged market capitalization. Effective spread is computed using the second-based TAQ data from 1993 until the millisecond TAQ data becomes available in 2003. Implementation shortfall – the blue line – is the difference, or slippage, between the arrival price and the execution price for a trade. The plot shows average implementation shortfall from 2009 through 2021, using data from ITG and Virtu Financial, for midcap stocks.

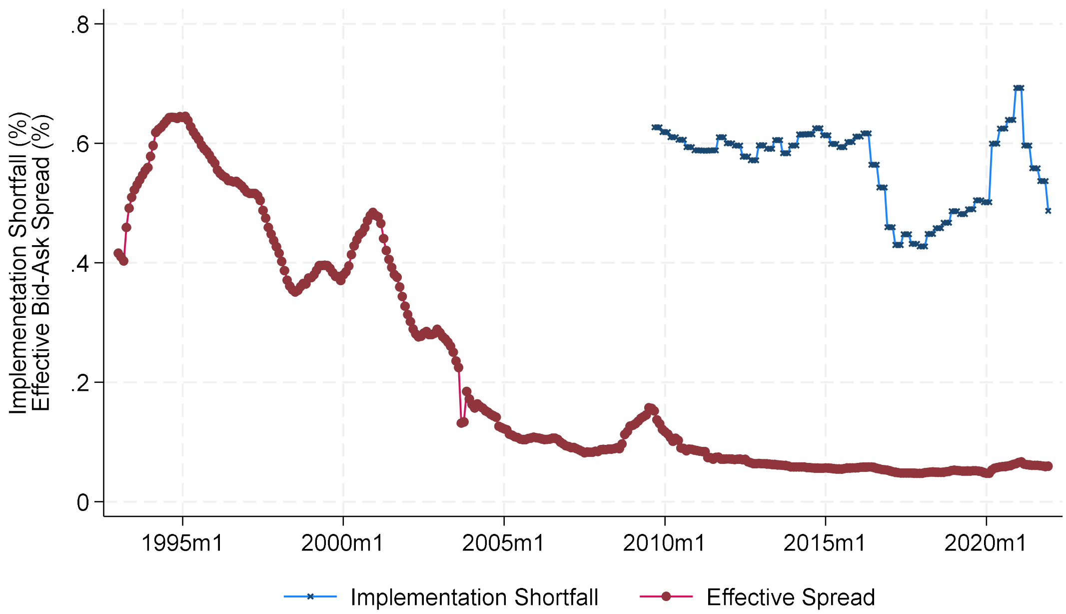


Table 1. S&P 500 Addition and deletion cumulative abnormal returns by year.

Announcement returns (Ann.) are the cumulative abnormal returns from the day before to the day after the announcement. Effective returns (Eff.) are the cumulative abnormal returns from the day before to the day after the index change became effective. Total returns are the cumulative abnormal returns from the day before the announcement to the day after the index change became effective. The table reports means by year, as well as results pooling across each 10-year period (observations within each 10-year period are event-weighted). The second-to-last row of the table reports the difference in average returns between the 2000s and the 2010s, while the last row of the table reports the associated standard errors (White, 1980). All returns are market-adjusted. Entries of "-" denote periods with no observations. In the last 4 rows, ***, **, and * refer to significance at the 1, 5, and 10 percent levels.

	Additions Cumulative Abnormal Returns				Deletions Cumulative Abnormal Returns			
Year	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total
1980	5	5.90%	5.90%	5.90%	0	-	-	-
1981	15	3.76%	3.76%	3.76%	2	-1.25%	-1.25%	-1.25%
1982	22	3.03%	3.03%	3.03%	4	-3.42%	-3.42%	-3.42%
1983	8	3.10%	3.10%	3.10%	6	-2.75%	-2.75%	-2.75%
1984	28	1.75%	1.75%	1.75%	3	-8.38%	-8.38%	-8.38%
1985	26	2.04%	2.04%	2.04%	2	-30.39%	-30.39%	-30.39%
1986	23	4.28%	4.28%	4.28%	3	8.73%	8.73%	8.73%
1987	21	6.14%	6.14%	6.14%	2	-3.91%	-3.91%	-3.91%
1988	20	3.71%	3.71%	3.71%	5	-3.66%	-3.66%	-3.66%
1989	28	2.79%	3.33%	3.18%	12	-5.41%	-5.24%	-5.19%
1990	9	1.96%	2.01%	4.64%	4	-30.89%	-24.35%	-26.25%
1991	9	8.16%	5.12%	8.52%	4	-50.74%	-31.50%	-36.87%
1992	6	4.10%	3.39%	6.85%	5	-24.24%	-19.26%	-37.07%
1993	6	5.70%	5.28%	8.47%	3	-0.79%	-4.76%	-8.90%
1994	7	3.39%	1.02%	3.98%	6	-4.66%	0.27%	-8.12%
1995	14	2.97%	2.22%	5.67%	10	-5.91%	-7.51%	-14.17%
1996	16	4.67%	2.90%	7.88%	8	-6.32%	-2.65%	-9.51%
1997	14	6.41%	5.23%	10.07%	3	-8.32%	-1.23%	-8.93%
1998	23	5.19%	5.12%	9.21%	7	-9.92%	-0.68%	-8.07%
1999	30	5.43%	2.82%	6.46%	6	-16.14%	-6.71%	-14.63%
2000	35	7.21%	3.00%	9.81%	17	-13.83%	-5.12%	-16.71%
2001	22	3.78%	0.09%	5.49%	6	-8.81%	-5.09%	-11.27%
2002	15	3.72%	2.40%	6.35%	11	-9.08%	-3.99%	-11.50%
2003	7	2.54%	-0.16%	0.75%	3	-23.94%	-2.52%	-24.18%
2004	12	2.73%	2.01%	4.76%	6	-3.14%	-0.92%	-4.67%
2005	12	3.64%	0.93%	3.65%	2	-4.56%	-2.62%	-7.53%
2006	22	4.40%	1.77%	5.89%	6	-6.01%	-1.05%	-7.52%
2007	31	2.25%	1.47%	2.65%	4	2.41%	-0.10%	0.65%
2008	31	4.68%	1.41%	5.64%	14	-21.25%	-13.90%	-24.46%
2009	24	2.48%	-0.84%	1.50%	16	-3.52%	-2.68%	-4.63%
2010	13	2.31%	-1.49%	-0.59%	3	0.74%	4.34%	5.77%
2011	8	0.17%	-1.00%	-1.87%	9	1.03%	0.25%	-1.78%
2012	5	4.61%	-1.33%	3.11%	5	-1.71%	-2.58%	-4.19%
2013	11	2.45%	1.54%	3.01%	10	-1.40%	2.95%	0.76%
2014	8	1.79%	0.07%	0.68%	8	2.71%	-0.62%	2.71%
2015	19	2.08%	0.46%	2.56%	6	-2.04%	-1.69%	0.47%
2016	21	0.24%	-1.06%	-0.53%	7	4.18%	1.67%	6.31%

	Additions Cumulative Abnormal Returns				Deletions Cumulative Abnormal Returns			
Year	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total
2017	20	0.77%	0.13%	0.10%	12	1.40%	-0.93%	-0.27%
2018	21	0.26%	0.76%	-0.83%	7	-0.35%	-0.08%	-2.77%
2019	15	-0.70%	1.57%	0.47%	10	-6.87%	0.18%	-6.09%
2020	12	0.40%	2.31%	5.49%	10	1.11%	-0.77%	-2.70%
1980s	196	3.36%***	3.44%***	3.42%***	39	-4.71%**	-4.65%**	-4.64%**
1990s	134	4.94%***	3.55%***	7.39%***	56	-13.91%***	-8.52%***	-16.11%***
2000s	211	4.06%***	1.35%***	5.16%***	85	-10.21%***	-4.99%***	-12.39%***
2010s	153	1.02%***	0.26%	0.83%	87	-0.18%	0.13%	-0.62%
2010s vs. 2000s		-3.04%***	-1.09%***	-4.33%***		10.03%***	5.12%***	11.77%***
(SE)		(0.52)	(0.54)	(0.93)		(2.29)	(2.16)	(2.56)

Table 2. Cumulative abnormal returns, controlling for characteristics.

We estimate the following multivariate regression separately for additions and deletions:

$$CAR_{it} = b_1 turn_{i,t-1} + b_2\, size_{i,t-1} + b_3 WZ_{i,t-1} + b_4 cover_{i,t-1} + \sum_{k=1}^{4} \gamma_k 1_{era=k} + e_{it},$$

where CAR_{it} is the cumulative abnormal return from the day before the announcement date to the day after the implementation date, measured in percent. $turn_{i,t-1}$ is the average turnover (defined as volume divided by shares outstanding) in stock *i* over the month before the index change, minus the value-weighted average turnover across all ordinary common shares traded on major exchanges in CRSP over the same period. $size_{i,t-1}$ is the firm's market capitalization on the last day before the announcement of the index change relative to the total market capitalization of the S&P 500 on the same day. $WZ_{i,t-1}$ is Wurgler and Zhuravskaya (2002)'s measure of arbitrage risk: the variance of CAPM regression residuals over the year before the announcement of index addition or deletion. $Cover_{i,t-1}$ is the number of analysts covering the stock during the last earnings announcement before the index change. All characteristics have been demeaned. $1_{era=k}$ are dummy variables for 10-year periods. Robust standard errors in parenthesis (White, 1980). The rows labeled e.g., 2010s vs. 1980s are the differences in the coefficients between these two eras. P-values from an F-test on equality of the γ_k coefficients reported below the differences and are shown in square brackets. ***, **, and * refer to significance at the 1, 5, and 10 percent levels.

	CAR Additions (%)		CAR Deletions (%)	
	(1)	(2)	(3)	(4)
$turn_{i,t-1}$		-0.14		-0.637
		(0.49)		(1.03)
$size_{i,t-1}$		19.08***		28.45*
		(4.15)		(16.46)
$WZ_{i,t-1}$		3,868***		-2183
		(1173.00)		(1590.00)
$cover_{i,t-1}$		-0.0289		0.0863
		(0.06)		(0.17)
1980-1989	3.654***	4.594***	-2.184	-0.388
	(0.35)	(0.58)	(2.69)	(3.20)
1990-1999	7.414***	7.388***	-15.20***	-13.09***
	(0.78)	(0.86)	(2.40)	(2.34)
2000-2009	4.950***	4.592***	-12.71***	-9.517***
	(0.70)	(0.61)	(2.37)	(1.80)
2010-2020	0.782	1.765***	-0.62	1.5
	(0.55)	(0.61)	(1.12)	(1.96)
N	610	610	237	237
R-squared	0.261	0.352	0.28	0.314
2010s vs. 1980s	-2.872	-2.829	1.564	1.889
[p-value]	[0.000]	[0.000]	[0.592]	[0.629]
2010s vs. 1990s	-6.632	-5.623	14.58	14.59
[p-value]	[0.000]	[0.000]	[0.000]	[0.000]
2010s vs. 2000s	-4.168	-2.827	12.09	11.02
[p-value]	[0.000]	[0.000]	[0.000]	[0.000]

Table 3. Difference in cumulative abnormal returns between direct additions and migrations

Mean cumulative abnormal return from the day before the announcement to the day after the implementation for migrations vs. direct additions and deletions, as well as the average difference between each of these returns in each sub-period. Standard error from two-sided t-test reported below the means.

		Additions CAR (%)			Deletions CAR (%)		
		Direct	Migrations	Diff.	Direct	Migrations	Diff.
1995-1999	Mean	10.23%	6.65%	-3.58%	-12.78%	-0.17%	12.61%
	(SE)	(7.69%)	(10.41%)	(2.12%)	(10.85%)	(4.98%)	(7.82%)
2000-2009	Mean	8.80%	2.72%	-6.07%	-15.71%	-4.10%	11.61%
	(SE)	(9.65%)	(9.29%)	(1.34%)	(25.61%)	(6.16%)	(6.29%)
2010-2020	Mean	5.40%	-1.82%	-7.22%	-6.86%	0.06%	6.92%
	(SE)	(8.38%)	(3.77%)	(0.99%)	(24.44%)	(8.45%)	(4.15%)

Table 4. Cumulative pre-announcement abnormal returns.

Mean cumulative abnormal returns from t=n to t=-1 or to +10 relative to the announcement, where n is either -100, -50, -20 or -10. Additions and deletions are shown separately.

	Time relative to announcement		Mean CAR (%) 1980-1989	1990-1999	2000-2009	2010-2020
Cumulative abnormal returns: Additions	-100	-1	6.91%	9.60%	14.16%	18.68%
	-50	-1	2.71%	2.49%	5.96%	6.61%
	-20	-1	0.81%	1.54%	1.99%	2.35%
	-10	-1	0.39%	0.88%	1.31%	0.96%
	-100	10	10.65%	17.21%	17.41%	19.79%
	-50	10	6.37%	9.29%	9.37%	7.20%
	-20	10	4.24%	8.18%	5.41%	3.01%
	-10	10	3.89%	7.31%	4.80%	1.60%
Cumulative abnormal returns: Deletions	-100	-1	-2.81%	-15.68%	-20.10%	-22.33%
	-50	-1	-1.53%	-11.21%	-18.54%	-11.44%
	-20	-1	-5.55%	-5.56%	-13.12%	-3.03%
	-10	-1	-2.59%	-4.45%	-10.69%	-1.80%
	-100	10	-6.51%	-25.75%	-22.93%	-22.16%
	-50	10	-6.03%	-21.08%	-22.32%	-11.39%
	-20	10	-10.35%	-15.93%	-18.35%	-3.05%
	-10	10	-7.72%	-14.95%	-16.06%	-1.67%

Table 5. Index effect decomposition.

Estimates of multiplier M and elasticity -1/M based on

$$\overline{CAR} = M \times (w \cdot \overline{D}_{Migrations} + (1-w) \cdot \overline{D}_{NonMigrations})$$

In the first 6 rows, CAR is measured as the cumulative abnormal return from the day before the announcement to the day after the implementation. In the next 6 rows, CAR is measured as the cumulative abnormal return from 20 days before the announcement to the day after the implantation. D (migrations) is the net demand by index trackers (expressed as a percentage of shares outstanding) minus the percentage of the S&P 400 MidCap owned by tracking funds. D(non-migrations) is the net purchases by index trackers. M is estimated by dividing the average abnormal return by the weighted mean of D. ε is the elasticity, equal to minus one divided by M. We estimate this separately for additions and deletions and by era.

Return Measure	Sample	Period	N	$\overline{CAR}$	$\overline{D}_{Migrations}$	$\overline{D}_{NonMig.}$	% migrations	$\overline{D}_{Wt.Mean}$	M	ε = -1/M
Baseline CAR = one day before announcement to one day after effective date	Additions	1995-1999	97	7.8%	1.11	1.24	69.07%	1.15	6.75	-0.15
		2000-2009	211	5.2%	0.71	2.49	59.24%	1.44	3.58	-0.28
		2010-2020	153	0.8%	0.31	5.61	63.40%	2.25	0.37	-2.72
	Deletions	1995-1999	34	-11.4%	-0.94	-1.07	5.88%	-1.06	10.76	-0.09
		2000-2009	85	-12.4%	-0.72	-2.50	20.00%	-2.15	5.77	-0.17
		2010-2020	87	-0.6%	-0.22	-5.53	87.36%	-0.89	0.70	-1.44
Extended CAR= 20 days before announcement to 1 day after effective	Additions	1995-1999	97	10.3%	1.11	1.24	69.07%	1.15	8.98	-0.11
		2000-2009	211	6.5%	0.71	2.49	59.24%	1.44	4.52	-0.22
		2010-2020	153	3.0%	0.31	5.61	63.40%	2.25	1.34	-0.75
	Deletions	1995-1999	34	-15.7%	-0.94	-1.07	5.88%	-1.06	14.74	-0.07
		2000-2009	85	-19.9%	-0.72	-2.50	20.00%	-2.15	9.25	-0.11
		2010-2020	87	-2.9%	-0.22	-5.53	87.36%	-0.89	3.29	-0.30

Table 6. Effect of controls on elasticity estimates.

We estimate the following multivariate regression separately for additions and deletions:

$$CAR_{it} = b_1 turn_{i,t-1} + b_2\, size_{i,t-1} + b_3 WZ_{i,t-1} + b_4 cover_{i,t-1} + \sum_{k=1}^{3} \gamma_k 1_{era=k} \times D_{era=k} + e_{it},$$

where in Columns 1-2 and 5-6, CAR_{it} is the cumulative abnormal return from the day before the announcement to the day after the implementation, measured in percent, while in Columns 3-4 and 7-8, CAR_{it} is the cumulative abnormal return from 20 days before the announcement to the day after the implementation. $turn_{i,t-1}$ is the average turnover (defined as volume divided by shares outstanding) in stock *i* over the month before the index change, minus the value-weighted average turnover across all ordinary common shares traded on major exchanges in CRSP over the same period. $size_{i,t-1}$ is the firm's market capitalization on the last day before the announcement of the index change relative to the total market capitalization of the S&P 500 on the same day. $WZ_{i,t-1}$ is Wurgler and Zhuravskaya (2002) measure of arbitrage risk: the variance of CAPM regression residuals over the year before the announcement of index addition or deletion. $Cover_{i,t-1}$ is the number of analysts covering the stock in the last earnings announcement before the index change. All characteristics have been demeaned. $1_{era=k}$ are dummy variables for 10-year periods. $D_{era=k}$ are variables equal to the average *net* demand shock (*D* (weighted mean) in Table 6) each period. Robust standard errors in parenthesis (White, 1980). ***, **, and * refer to significance at the 1, 5, and 10 percent levels.

	Additions *CAR*				Deletions *CAR*			
	Ann-1→Eff+1		Ann-20→Eff+1		Ann-1→Eff+1		Ann-20→Eff+1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$turn_{i,t-1}$		-0.0858		-0.60		-0.578		1.081
		(0.518)		(0.689)		(1.040)		(1.335)
$size_{i,t-1}$		20.69***		20.36***		35.18		70.04**
		(3.931)		(4.680)		(24.130)		(32.080)
$WZ_{i,t-1}$		3,856***		4,234**		-1,156		-6,059***
		(1222)		(1658)		(1852)		(1581)
$cover_{i,t-1}$		-0.0293		-0.0891		0.0623		-0.128
		(0.067)		(0.091)		(0.177)		(0.219)
1995 - 1999 x Avg. demand shock	6.779***	6.640***	9.120***	8.712***	10.90***	8.709***	14.99***	10.85***
	(0.868)	(0.934)	(1.350)	(1.389)	(1.868)	(2.329)	(3.123)	(3.686)
2000-2009 x Avg. demand shock	3.441***	3.116***	4.227***	3.869***	5.540***	4.400***	9.433***	6.544***
	(0.487)	(0.431)	(0.671)	(0.653)	(1.043)	(0.815)	(1.258)	(1.167)
2010-2020 x Avg. demand shock	0.348	0.726***	1.307***	1.749***	0.696	-1.893	3.290*	0.686
	(0.246)	(0.276)	(0.374)	(0.472)	(1.258)	(2.325)	(1.918)	(2.965)
N	451	451	451	451	200	200	200	200
R-squared	0.231	0.34	0.202	0.251	0.257	0.277	0.345	0.423

Table 7. Net buying and selling by trackers and institutional investors.

Net buying and selling by trackers are defined as the total change in split-adjusted shares held by index trackers between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding (multiplied by 100). Net buying and selling by institutions (Insts.) is defined as the total change in split-adjusted shares held by 13F filing institutions between the quarter before and the quarter after the index change, divided by split-adjusted shares outstanding. Net buying by active and passive mutual funds is defined similarly. We compute the median of this quantity among additions and deletions each year. The final row represents an equal weighted average across the yearly medians. Entries of "-" denote periods with no observations.

	Additions (median by year)				Deletions (median by year)			
Year	Trackers	Passive	Active	Insts.	Trackers	Passive	Active	Insts.
1980	0.01%	0.01%	0.41%	-0.18%	-	-	-	-
1981	0.01%	0.01%	-0.03%	0.91%	-0.01%	-0.01%	0.54%	-0.08%
1982	0.01%	0.01%	0.35%	3.40%	-0.01%	-0.01%	0.18%	-3.07%
1983	0.02%	0.02%	0.11%	0.54%	-0.02%	-0.02%	-0.48%	0.47%
1984	0.02%	0.02%	-0.14%	2.43%	-0.01%	-0.01%	-0.09%	0.24%
1985	0.03%	0.03%	-0.25%	2.48%	-0.01%	-0.01%	-4.65%	-10.14%
1986	0.03%	0.03%	0.48%	3.51%	-0.02%	-0.02%	-2.52%	-21.12%
1987	0.05%	0.05%	0.14%	1.37%	-0.05%	-0.05%	3.75%	-4.12%
1988	0.06%	0.05%	0.42%	3.24%	-0.06%	-0.05%	-8.49%	-36.75%
1989	0.10%	0.07%	0.08%	2.22%	-0.07%	-0.06%	-2.35%	-18.13%
1990	0.15%	0.10%	1.14%	0.54%	-0.15%	-0.06%	-1.92%	-11.76%
1991	0.23%	0.19%	0.24%	1.55%	-0.12%	-0.11%	-1.11%	-5.76%
1992	0.28%	0.23%	0.33%	2.21%	-0.16%	-0.14%	-0.09%	-4.22%
1993	0.46%	0.34%	0.66%	1.38%	-0.41%	-0.34%	-0.49%	-1.18%
1994	0.57%	0.41%	-0.55%	0.77%	-0.66%	-0.40%	-0.01%	-3.97%
1995	0.68%	0.55%	0.60%	2.61%	-0.66%	-0.41%	0.76%	-3.02%
1996	1.11%	0.95%	-0.66%	0.27%	-1.03%	-0.72%	1.43%	-1.17%
1997	1.37%	1.15%	0.65%	0.27%	-1.36%	-0.76%	0.28%	1.88%
1998	1.47%	1.36%	0.14%	0.89%	-1.24%	-0.94%	-3.62%	-0.57%
1999	1.59%	1.49%	-1.01%	0.41%	-1.45%	-1.30%	-0.86%	-10.71%
2000	1.61%	1.58%	2.06%	1.36%	-1.56%	-0.80%	-2.29%	-3.47%
2001	1.08%	1.05%	-0.79%	0.42%	-0.91%	-0.03%	-0.29%	1.81%
2002	1.36%	1.25%	0.01%	-0.06%	-1.19%	-1.23%	-0.14%	-2.00%
2003	2.15%	1.70%	-1.85%	-1.09%	-2.01%	-1.82%	-1.93%	3.69%
2004	2.42%	1.49%	-0.73%	0.93%	-2.34%	-1.23%	0.25%	0.52%
2005	2.70%	1.43%	-0.74%	-0.20%	-3.29%	-3.17%	0.83%	-2.01%
2006	2.63%	1.82%	-0.05%	0.36%	-3.07%	-2.08%	-1.41%	-3.77%
2007	2.80%	1.66%	0.40%	0.69%	-2.88%	-1.04%	2.62%	-1.94%
2008	3.84%	2.09%	0.90%	1.55%	-3.45%	-2.46%	-8.55%	-7.35%
2009	3.76%	1.82%	0.25%	0.70%	-4.11%	-3.46%	-1.89%	-4.16%
2010	3.86%	1.57%	0.45%	1.01%	-4.28%	-1.09%	0.90%	3.56%
2011	4.11%	0.79%	1.11%	0.30%	-4.51%	-0.92%	-0.93%	-0.25%
2012	4.28%	2.65%	-4.49%	0.73%	-0.03%	0.33%	2.19%	-0.07%
2013	4.69%	1.25%	0.09%	1.86%	-4.78%	-1.28%	0.71%	0.45%
2014	4.97%	1.31%	0.07%	2.49%	-5.34%	-1.41%	1.89%	2.64%
2015	5.34%	2.12%	0.19%	1.11%	-6.32%	-3.00%	-3.47%	-4.16%
2016	5.99%	1.16%	0.41%	0.59%	-6.50%	-1.75%	-0.87%	-2.97%
2017	6.35%	2.03%	2.46%	0.48%	-7.05%	-1.94%	-0.35%	0.32%
2018	7.43%	0.88%	0.92%	0.45%	-7.68%	-0.31%	-3.16%	-0.87%
2019	7.57%	0.99%	-0.60%	1.16%	-8.46%	-2.35%	-5.28%	-6.40%
2020	7.53%	2.55%	2.40%	0.65%	-8.45%	-2.29%	-5.23%	-1.42%
Mean	3.04%	1.29%	0.13%	0.85%	-3.08%	-1.24%	-1.03%	-2.20%

Table 8. Addition and deletion returns by year for other indices.

Mean cumulative abnormal returns (*CAR*) for additions to other indices. For direct additions to the Russell 2000 (R2 Addition) and Russell 1000 (R1 Addition), CAR_{it} is the cumulative market-adjusted return from the day before the ranking date in May to the day after the implementation, typically in June. For the MidCap, SmallCap and Nasdaq 100, only direct additions/deletions are included. In these cases, CAR_{it} is the cumulative market-adjusted return from 10 days before the effective date to one day after the effective date. Standard errors, clustered by year, reported in parenthesis. P-values from an F-test of equality of the γ_k coefficients is reported below the differences in the coefficients in square brackets. ***, **, and * refer to significance at the 1, 5, and 10 percent levels.

	Russell		S&P MidCap		S&P SmallCap		Nasdaq 100		All	
	Addition 1000	Addition 2000	Addition	Deletion	Addition	Deletion	Addition	Deletion	Addition	Deletion
	(1)	(2)	(5)	(6)	(7)	(8)	(3)	(4)	(9)	(10)
1990s	1.011	2.215*	5.624***	-4.528**	6.342***	-6.694***	3.876	0.171	2.459*	-2.603***
	(1.317)	(1.238)	(1.591)	(1.777)	(1.032)	(0.640)	(3.276)	(1.537)	(1.275)	(0.203)
2000s	16.973*	8.284*	8.333***	-18.252***	7.026***	-24.589***	2.562**	-2.622	8.226**	-16.711***
	(9.546)	(4.594)	(1.475)	(5.024)	(0.859)	(3.522)	(1.090)	(1.767)	(3.876)	(2.259)
2010s	8.532	3.148**	5.665***	-1.247	6.025***	-12.179***	1.976*	0.325	4.001***	-6.443***
	(5.114)	(1.421)	(1.123)	(2.478)	(0.735)	(1.606)	(1.140)	(0.678)	(1.286)	(0.952)
N	456	7,769	490	137	1,203	322	317	257	10,235	716
R-squared	0.165	0.05	0.314	0.331	0.284	0.431	0.062	0.017	0.065	0.267
2000s vs. 1990s	15.962	6.069	2.709	-13.724**	0.684	-17.895***	-1.314	-2.793	5.767	-14.108***
[p-value]	[0.108]	[0.294]	[0.983]	[0.016]	[0.615]	[0.004]	[0.713]	[0.132]	[0.611]	[0.000]
2010s vs. 2000s	-8.441	-5.136	-2.668	17.005	-1.001	12.410***	-0.586	2.947	-4.225**	10.268***
[p-value]	[0.442]	[0.624]	[0.162]	[0.292]	[0.385]	[0.000]	[0.707]	[0.244]	[0.040]	[0.001]
2010s vs. 1990s	7.521	0.933	0.041	3.281***	-0.317	-5.485***	-1.900	0.154	1.542**	-3.840***
[p-value]	[0.165]	[0.212]	[0.223]	[0.006]	[0.805]	[0.004]	[0.589]	[0.928]	[0.023]	[0.000]

Figure A1. Alternative method of identifying S&P 500 trackers.

Each year, we identify S&P 500 index funds based on names and objective codes. To identify funds based on objective codes we use CRSP objective codes SP and SPSP. To identify funds based on names we use variants of "S&P 500", "S and P 500" and "SP 500". Finally, we add up the total assets of these funds, and divide them by the total market capitalization of the S&P 500 index.

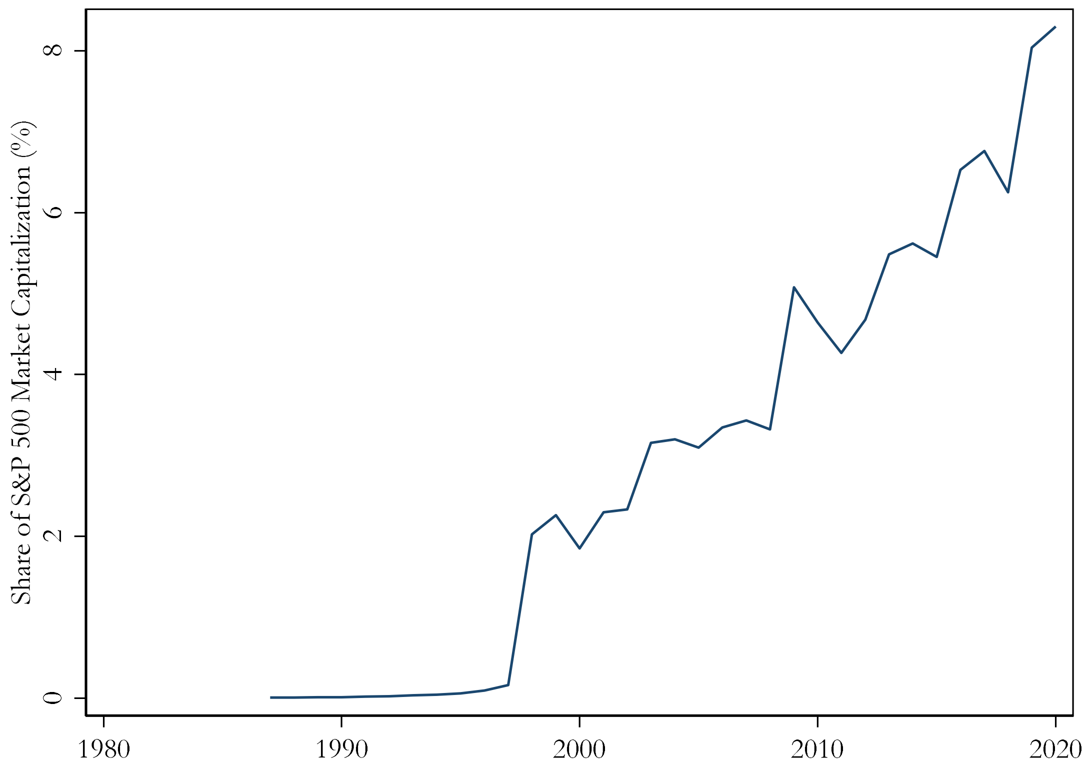


Table A1. Sample selection

We report the total number of S&P 500 index additions and deletions each year that can be matched from Siblis to CRSP. We also report the number of firms in our final sample, which excludes those that are listed, acquired, delisted for reasons other than acquisition, or are acquired within 100 days of the index change. Our filters also exclude firms which cannot be matched to the Thompson S12 data in either the quarter before or after the index change or have missing returns around the time of the index change. Entries of "-" denote periods with no observations.

Year	Total Additions	Additions Sample	% Included	Total Deletions	Deletions Sample	% Included
1980	11	5	45%	-	-	-
1981	21	15	71%	3	2	67%
1982	27	22	81%	13	4	31%
1983	11	8	73%	11	6	55%
1984	30	28	93%	12	3	25%
1985	28	26	93%	11	2	18%
1986	28	23	82%	16	3	19%
1987	25	21	84%	13	2	15%
1988	25	20	80%	22	5	23%
1989	29	28	97%	27	12	44%
1990	12	9	75%	13	4	31%
1991	12	9	75%	12	4	33%
1992	7	6	86%	7	5	71%
1993	11	6	55%	10	3	30%
1994	17	7	41%	17	6	35%
1995	29	14	48%	29	10	34%
1996	22	16	73%	22	8	36%
1997	26	14	54%	26	3	12%
1998	40	23	58%	40	7	18%
1999	39	30	77%	41	6	15%
2000	56	35	63%	55	17	31%
2001	30	22	73%	30	6	20%
2002	23	15	65%	24	11	46%
2003	9	7	78%	8	3	38%
2004	19	12	63%	19	6	32%
2005	18	12	67%	18	2	11%
2006	32	22	69%	29	6	21%
2007	38	31	82%	39	4	10%
2008	37	31	84%	36	14	39%
2009	26	24	92%	26	16	62%
2010	15	13	87%	16	3	19%
2011	20	8	40%	20	9	45%
2012	17	5	29%	17	5	29%
2013	19	11	58%	19	10	53%
2014	16	8	50%	14	8	57%
2015	27	19	70%	24	6	25%
2016	28	21	75%	28	7	25%
2017	26	20	77%	27	12	44%
2018	24	21	88%	23	7	30%
2019	21	15	71%	21	10	48%
2020	16	12	75%	16	10	63%
Average	24	16	68%	23	7	34%
Total	967	694		854	267	

Table A2. Sensitivity of abnormal returns to sample selection.

Our sample excludes firms that are listed, acquired, delisted for reasons other than acquisition, or are acquirers within 100 days of the index change. We also exclude firms that cannot be matched to the Thompson S12 data in either the quarter before or after the index change or have missing returns around the time of the index change announcement or implementation. Announcement returns (Ann.) are the cumulative abnormal returns from the day before to the day after the announcement. Effective returns (Eff.) are the cumulative abnormal returns from the day before to the day after the index change became effective. Total returns are the cumulative abnormal returns from the day before the announcement to the day after the index change became effective. Returns are market-adjusted. Entries of "-" denote periods with no observations.

	Additions Cumulative Abnormal Return								Deletions Cumulative Abnormal Return							
	Our Sample				Full Sample				Our Sample				Full Sample			
Year	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total
1980	5	5.90%	5.90%	5.90%	11	4.27%	4.27%	4.27%	-	-	-	-	-	-	-	-
1981	15	3.76%	3.76%	3.76%	21	3.26%	3.26%	3.26%	2	-1.25%	-1.25%	-1.25%	3	-3.51%	-3.51%	-3.51%
1982	22	3.03%	3.03%	3.03%	27	2.60%	2.60%	2.60%	4	-3.42%	-3.42%	-3.42%	13	-2.06%	-2.06%	-2.06%
1983	8	3.10%	3.10%	3.10%	11	3.07%	3.07%	3.07%	6	-2.75%	-2.75%	-2.75%	11	-2.08%	-2.08%	-2.08%
1984	28	1.75%	1.75%	1.75%	30	1.72%	1.72%	1.72%	3	-8.38%	-8.38%	-8.38%	12	-2.73%	-2.73%	-2.73%
1985	26	2.04%	2.04%	2.04%	28	1.92%	1.92%	1.92%	2	-30.39%	-30.39%	-30.39%	11	-5.83%	-5.83%	-5.83%
1986	23	4.28%	4.28%	4.28%	28	4.02%	4.02%	4.02%	3	8.73%	8.73%	8.73%	16	1.51%	1.51%	1.51%
1987	21	6.14%	6.14%	6.14%	25	5.65%	5.65%	5.65%	2	-3.91%	-3.91%	-3.91%	13	-1.26%	-1.26%	-1.26%
1988	20	3.71%	3.71%	3.71%	25	3.75%	3.75%	3.75%	5	-3.66%	-3.66%	-3.66%	22	-1.85%	-1.85%	-1.85%
1989	28	2.79%	3.33%	3.18%	29	2.76%	3.28%	3.14%	12	-5.41%	-5.24%	-5.19%	27	-2.27%	-2.23%	-2.52%
1990	9	1.96%	2.01%	4.64%	12	1.55%	1.88%	3.39%	4	-30.89%	-24.35%	-26.25%	13	-7.95%	-6.52%	-6.57%
1991	9	8.16%	5.12%	8.52%	12	6.69%	4.13%	6.73%	4	-50.74%	-31.50%	-36.87%	12	-16.49%	-11.85%	-12.10%
1992	6	4.10%	3.39%	6.85%	7	4.10%	2.19%	5.16%	5	-24.24%	-19.26%	-37.07%	7	-16.30%	-12.88%	-25.61%
1993	6	5.70%	5.28%	8.47%	11	4.07%	2.53%	4.83%	3	-0.79%	-4.76%	-8.90%	10	0.92%	-1.60%	-2.26%
1994	7	3.39%	1.02%	3.98%	17	2.21%	0.90%	3.71%	6	-4.66%	0.27%	-8.12%	17	-1.41%	0.77%	-1.97%
1995	14	2.97%	2.22%	5.67%	29	3.56%	2.32%	4.93%	10	-5.91%	-7.51%	-14.17%	29	-2.21%	-2.18%	-4.80%
1996	16	4.67%	2.90%	7.88%	22	4.64%	2.23%	6.58%	8	-6.32%	-2.65%	-9.51%	22	-3.40%	-0.55%	-3.87%
1997	14	6.41%	5.23%	10.07%	26	6.39%	4.69%	8.17%	3	-8.32%	-1.23%	-8.93%	26	-0.49%	-0.03%	-0.66%
1998	23	5.19%	5.12%	9.21%	40	5.69%	2.81%	7.89%	7	-9.92%	-0.68%	-8.07%	40	-1.19%	-0.97%	-1.09%
1999	30	5.43%	2.82%	6.46%	39	5.17%	3.20%	7.58%	6	-16.14%	-6.71%	-14.63%	41	-1.25%	-1.07%	-0.99%
2000	35	7.21%	3.00%	9.81%	56	5.90%	1.89%	8.71%	17	-13.83%	-5.12%	-16.71%	55	-3.91%	-1.96%	-4.96%
2001	22	3.78%	0.09%	5.49%	30	3.48%	0.01%	4.41%	6	-8.81%	-5.09%	-11.27%	30	-7.01%	-2.43%	-6.02%
2002	15	3.72%	2.40%	6.35%	23	3.26%	1.70%	4.90%	11	-9.08%	-3.99%	-11.50%	24	-11.06%	-7.11%	-12.21%
2003	7	2.54%	-0.16%	0.75%	9	2.38%	0.63%	1.34%	3	-23.94%	-2.52%	-24.18%	8	-8.23%	0.31%	-7.62%
2004	12	2.73%	2.01%	4.76%	19	1.61%	1.07%	4.52%	6	-3.14%	-0.92%	-4.67%	19	-0.20%	-0.52%	-0.30%
2005	12	3.64%	0.93%	3.65%	18	3.29%	1.56%	3.94%	2	-4.56%	-2.62%	-7.53%	18	-8.38%	-8.73%	-11.06%
2006	22	4.40%	1.77%	5.89%	32	3.97%	0.35%	3.57%	6	-6.01%	-1.05%	-7.52%	29	-2.02%	-2.25%	-3.73%
2007	31	2.25%	1.47%	2.65%	38	1.99%	0.81%	2.02%	4	2.41%	-0.10%	0.65%	39	0.26%	0.57%	0.78%

	Additions Cumulative Abnormal Return								Deletions Cumulative Abnormal Return							
	Our Sample				Full Sample				Our Sample				Full Sample			
Year	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total	N	Ann.	Eff.	Total
2008	31	4.68%	1.41%	5.64%	37	4.53%	1.10%	4.76%	14	-21.25%	-13.90%	-24.46%	36	-10.31%	-8.21%	-12.12%
2009	24	2.48%	-0.84%	1.50%	26	2.20%	-1.00%	0.97%	16	-3.52%	-2.68%	-4.63%	26	-4.33%	-2.35%	-5.96%
2010	13	2.31%	-1.49%	-0.59%	15	2.55%	-1.38%	-0.18%	3	0.74%	4.34%	5.77%	16	-0.50%	0.06%	-0.02%
2011	8	0.17%	-1.00%	-1.87%	20	0.47%	-0.87%	-0.22%	9	1.03%	0.25%	-1.78%	20	0.39%	0.64%	-0.38%
2012	5	4.61%	-1.33%	3.11%	17	2.54%	-1.17%	1.15%	5	-1.71%	-2.58%	-4.19%	17	-0.85%	-1.42%	-1.74%
2013	11	2.45%	1.54%	3.01%	19	2.01%	0.98%	1.90%	10	-1.40%	2.95%	0.76%	19	-0.25%	1.35%	0.53%
2014	8	1.79%	0.07%	0.68%	16	2.36%	-0.43%	0.78%	8	2.71%	-0.62%	2.71%	14	1.89%	-0.20%	1.78%
2015	19	2.08%	0.46%	2.56%	27	1.10%	0.23%	1.57%	6	-2.04%	-1.69%	0.47%	24	-1.49%	0.03%	-0.15%
2016	21	0.24%	-1.06%	-0.53%	28	0.90%	-1.14%	0.07%	7	4.18%	1.67%	6.31%	28	2.01%	-0.47%	1.90%
2017	20	0.77%	0.13%	0.10%	26	0.57%	-0.40%	-0.21%	12	1.40%	-0.93%	-0.27%	27	1.12%	-1.36%	-0.33%
2018	21	0.26%	0.76%	-0.83%	24	0.06%	0.51%	-1.16%	7	-0.35%	-0.08%	-2.77%	23	0.19%	0.46%	-0.28%
2019	15	-0.70%	1.57%	0.47%	21	-0.51%	1.40%	0.51%	10	-6.87%	0.18%	-6.09%	21	-3.68%	-0.30%	-3.79%
2020	12	0.40%	2.31%	5.49%	16	-1.49%	-0.29%	2.04%	10	1.11%	-0.77%	-2.70%	16	0.75%	-0.37%	-1.90%