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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 3.4% in the 1980s and 7.6% in the 1990s to 0.8% over the past decade. This has occurred despite a significant increase in the percentage of stock market assets linked to the index. A similar pattern has occurred for index deletions, with large negative abnormal returns on average during the 1980s and 1990s, but only -0.6% between 2010 and 2020. We investigate potential drivers of this surprising phenomenon and discuss the implications for market efficiency.

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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 the index change. Since then, an extensive literature has documented similar price impact in other stock indexes 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 pre-1976 than 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 that 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 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:

$$Price\ Impact_{it} = \left(\frac{-1}{Demand\ \text{Elasticity}}\right) \times Demand\ Shock_{it} \tag{1}$$

where $Price\ Impact_{it}$ denotes the percentage change in price, and $Demand\ Shock_{it}$ refers to the percentage of capitalization of stock i bought upon index addition or sold upon index deletion. Given the rise of indexation, this logic would predict substantially growing price impact from the 1980s onwards.

[1] See e.g., Warther (1995), Mitchell, Pulvino and Stafford (2005), Ben-Rephael, Kandel and Wohl (2010), Lou, Yan and Zhang (2013) and Hartzmark and Solomon (2022).

Conforming with 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 7.6% in the 1990s. Surprisingly, however, and consistent with Bennett, Stulz and Wang (2020), we show that the average price impact fell somewhat in the first decade of the 2000s to 5.2%, and then fell to 0.8% in the last 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, -16.6% in the 1990s, -12.3% from 2000-2009, and -0.6% from 2010-2020. Again, the average return in the past decade is not statistically distinguishable from zero.

Why did the S&P 500 index effect seemingly disappear? And if so, can we interpret this change from the lens of market efficiency? We consider five broad classes of explanation:

1) Changing composition of additions and deletions. 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 in the spirit of Fama and French (2001) to show that changes in the composition (as measured by volatility, trading volume, and size relative to total index capitalization) cannot fully account for changes in the average index addition and deletion returns that we have observed since 2010.

2) The stock market is more liquid overall today than in the past. Under this explanation, there is nothing unique about S&P 500 additions and deletions per se, it is simply that trading costs in all settings have declined, perhaps because of more trading volume or market-making capacity. Drawing on a variety of different estimates, we show that trading costs have indeed fallen considerably since the early 1990s. Specifically, value-weighted average bid-ask spreads have fallen by a factor of about 10× between the early 1990s and the late 2010s and implementation shortfall – a measure of trading costs for large institutional

investors -- has decreased substantially. These declines in trading costs, however, are not enough to fully explain the change in price impact, and moreover the timing of the decline in trading costs predates the disappearance of the index announcement effect.

3) A third class of explanation is that the *net* demand shock 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 40% of additions to over 80% and this trend toward more migrations is mirrored among S&P 500 index deletions.

The returns to migrations reflected the increasing importance of the S&P MidCap index over time. In the mid-1990s, migration and non-migration additions had average returns of 6.7% and 6.4%, respectively. By the late 2010s, however, direct additions had returns of 2.2%, while migrations had returns of -2.3%. This divergence coincides with the rise of MidCap-focused fund (Sammon and Shim, 2022). More speculatively, it seems possible that one of the reasons for an increased percentage of index migrations is that the S&P 500 index committee has sought to minimize large price impact associated with rebalancing trades.

4) A fourth 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. We find mixed evidence to support this hypothesis. In recent years, a larger share of the total return leading up to the index change occurs *before* announcement, although the reason for this is subject to interpretation. In addition, a simple rule of selecting largest eligible firm has become a better indicator of future S&P 500 addition, further suggestive evidence of predictability. That said, which precise stocks get added are still difficult to predict.

5) The fifth class of 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. While dispositive evidence for this explanation is hard to come by, there are a few markers that are consistent. For one, over the past 15 years, a number of Wall Street trading desks have increased personnel and computing resources devoted to index trading, with several large players (UBS, Goldman Sachs) with specialized sell side teams. Second, the distribution of trading volume has become more concentrated around index change events. Specifically, in the 1990s, in the month before and after the index change, 15% of total volume occurred on the effective date, while in the 2010s that number increased to almost 30%. Li (2021) shows that most ETFs track indices that pre-announce their rebalances and trade in the closing auction. This transparency may have made it easier for other investors to coordinate on liquidity provision (Chinco and Sammon, 2022). A last observation is that despite the large size of the demand shock experienced by adds and deletes, most 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, and in part by creating arrangements where other institutions stood ready to sell to indexers upon inclusions. This worked to eliminate the anomaly on average, in spite of 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, that they decline once they are well recognized by the market (McLean and Pontiff 2016).

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] 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. (2018), Buss and Sundaresan (2020), Ernst (2020), Malikov (2020), Lee (2020), 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. Most closely related to our paper is Bennett, Stulz, and Wang (2022), who first noted the decline in the index inclusion effect, although their focus is on the real effects of index changes, and they study only additions to the S&P 500 between 1997-2017.

The paper proceeds as follows. In Section I, 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 II considers, in turn, each of the five potential explanations. Section III concludes.

1. Index tracking and the index inclusion effect 1990-2020

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

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

[2] Wurgler and Zhuravskaya (2002); Other indices. Kaul, Mehrotra, Morck (2000); Madhavan (2003); Greenwood (2005); Chang, Liskovich, Hong (2015), Madhavan et. al. (2022).

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 752 of the 755 additions and 749 of the 750 deletions between Siblis and CRSP. Before 1990, Siblis does not provide information on announcement dates, so for the pre-1990 additions and deletions, we use data from Barberis, Shleifer and Wurgler (2005).

For purposes of measuring returns, the full sample we just described is sufficient.[3] But in order 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.[4] These filters exclude e.g., spin-offs, where a security can be added to the index and then quickly removed.

Columns 2 and 5 of Appendix Table A1 contain the number of observations we can match between Siblis and CRSP each year, while columns 3 and 6 contain the final sample size after we apply all our filters. The number of additions and deletions can differ slightly each year when S&P retains an extra security (because of these retentions, the S&P 500 currently has 505 securities) or due to the small number of observations we cannot match between CRSP and Siblis.

1.2 Identifying S&P 500 index trackers

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

[3] We have verified that our conclusions about returns are not sensitive to the sample. See Appendix Table A2.

[4] We exclude cases where the firm is an acquirer because if 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 by S&P 500 index-tracking funds.

times an added stock is not held by the fund the quarter before the addition, and the stock is held by the fund the quarter after addition. Similarly, we count the number of times a dropped stock is held by the fund the quarter before the addition, and the stock is not held by the fund the quarter after the addition. We then 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. While at first pass this threshold seems low, we believe it is reasonable given the quarterly nature of the S12 data, as well as the possibly stale data on fund holdings. For example, within-quarter changes in holdings are impossible to identify when holdings are only reported once a quarter. Further, the holdings data is often stale (i.e., there is a gap between RDATE and FDATE), which means that a true change in holdings in response to an index change may not show up in S12 data for several quarters, which our classification of tracking trades would miss.[5] 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 identifying funds based on their objective codes and names instead of changes in holdings.[6]

Having identified the S&P 500 tracking funds, we measure net buying and selling by these funds around index changes. To this end, we add up the shares held by all trackers the quarter before and after the index change. Then, we define net trading by trackers as:

$$Net\ Trading_{i,t} = 100\ \times (Shares\ held_{i,t+1} - Shares\ held_{i,t-1})/Shares\ outstanding_{i,t+1} \qquad (2)$$

[5] As a specific example, SPY, the largest S&P 500 ETF, only has annual data before 2008 (i.e., the same RDATE is used for four FDATEs each year), then switches to quarterly thereafter. So, for 3 quarters a year the holdings data are stale, making it hard to identify tracking trades.

[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.

where both shares held, and shares outstanding are split-adjusted using the CRSP cumulative factor to adjust shares outstanding.

Figure 1 shows the average net trading by trackers across adds and drops each year. Consistent with the aggregate rise of passive ownership, in the early 1990s, net buying by trackers of adds was close to 0% of shares outstanding, while now it is over 6%. This pattern is mirrored for drops, going from nearly nothing to selling constituting almost 8% of shares outstanding.

We believe our estimate of net trading by 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 may often trade like indices, but not often enough to be classified as index trackers by our method (Mauboussin, Callahan and Majd, 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 number.[7]

1.3. Inclusion and deletion returns

Figure 2 presents statistics on average returns for S&P 500 index additions and deletions by year. Table 1 presents statistics by year and Table 2 presents statistics based on 5-year periods. We define the abnormal return as:

$$AR_{it} = R_{it} - R_{S\&P\ 500,t} \tag{3}$$

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

[7] Author calculations by dividing predicted net purchases by market capitalization for index additions in 2022 UBS report.

according to (3) 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 total return, defined as the cumulative market-adjusted return from the last trading day before the announcement to the first trading day after the implementation.[8]

Panel A of Figure 2 plots the average index inclusion and deletion effect by year. For additions, the index inclusion effect was 3.42% in the early 1980s, increasing to 7.6% by the 1990s. This is where the effect peaked, as it declined to 5.21% by the 2000s before declining to a statistically insignificant 0.8% in the 2010s. 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 cumulative returns of -4.6%, while in the 90s, they had returns of -16.6%. The deletion effect fell in magnitude to -12.3% in the 2000s and disappeared in the 2010s, with an average 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.[9] 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.

In Table 2, we break the total index inclusion and deletion effect into the announcement return and the implementation return.[10] The 2nd row of Panel A shows that for additions, the announcement return has

[8] In principle, the total return 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.

[9] See Arnott, Kalesnik, Wu (2021) for further discussion.

[10] Note that in this table, the announcement return, and implementation return do not have to 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.

been declining over time. In the 1980s, it was 3.4%, falling to 4.1% by the 2000s and to 1% by the late 2010s. The 3rd row shows that this pattern is mirrored for effective day returns. Specifically, in the 1980s, the implementation return was around 2%, declining to 1% by the 2000s and close to zero by the late 2010s. The last column 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.

Panel B of Table 2 replicates Panel A, 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 consistent with the growing importance of index funds, but then declined slightly in the 2000s and disappeared, on average, in the 2010s, in spite of 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 mechanical buying, i.e., the net purchases by index trackers. 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 mechanical buying has a negative slope and an R-squared value of about 2%, while for deletions the same regression has a negative slope and an R-square value of roughly 6%.

2. Explanations

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

2.1 Explanation 1: changing composition of additions and deletions

So far, we have shown that the *average* returns of S&P 500 additions have been declining over time. One concern with these results is that this trend was driven by a change in the composition of the added and deleted firms, rather than a decline in the index inclusion effect itself. For example, it is well known that benchmarked investors are more likely to buy additions that are a large share of the index, as doing so helps them avoid tracking error.[11] 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 market-adjusted announcement return of 5.2% and implementation return of 4.5%.

Another potential shift might be changes in the volatility of additions and deletions. Theoretically, for a demand shock of a given size, price impact should be correlated with fundamental volatility (Kyle 1985, Chacko, Jurek, Stafford 2008). Shifts in this composition – such as for example the addition of high-risk internet stocks in the late 1990s – might explain some of our results.

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

$$Total\ Return_{it} = b_1 turn_{i,t-1} + b_2\ size_{i,t-1} + b_3\ vol_{i,(t-12,t-1)} + \sum_{k=1}^{4} \gamma_k 1_{era=k} + e_{it} \quad (4)$$

where $Total\ Return_{it}$ is the cumulative return from the day 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 changes. To account for the time-series trend toward increased trading volume, we subtract 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. We include this, rather than the level of market capitalization on its own, to account for time-variation in firm size and total index capitalization. $vol_{i,(t-12,t-1)}$ is a 12-month moving average of the sum of daily squared percentage market-

[11] This should not apply to explicit index trackers, who should aim to track the index perfectly, even for small additions.

adjusted stock returns computed each month.[12] Finally, $1_{era=k}$ are dummy variables for 10-year periods e.g., 1980-1989. Note that because we include separate dummies for each era, there is no constant term in the regression.

The first column of Table 3 contains the regression results for additions. 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, and 2000s, these coefficients are positive, and statistically significant for the 1990s and 2000s, suggesting that the index inclusion effect in the 1990s and 2000s was not entirely explained by these firm-level characteristics. Further, consistent with our previous results, these coefficients shrink from the 1990s to the 2000s. Finally, these coefficients become negative and significant in the 2010s.

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 weekly volume. The first row shows that, perhaps surprisingly, the effect of past turnover for additions is positive and weakly statistically significant. In terms of magnitudes, a 1% increase in past turnover would imply a roughly 1% bigger index inclusion effect.

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 over 18% larger inclusion effect. Admittedly, this is rare, because the average addition is 9bp of total index capitalization while the average deletion is 3bp of total index capitalization. Further, additions did shrink in relative size between 1980 to 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

[12] Results are nearly identical using a rolling standard deviation to measure volatility instead of the sum of squared returns.

decline in the index inclusion effect. The third control is prior stock-level volatility. Consistent with theory and Wurgler and Zhuravskaya (2002), volatility attracts a positive and significant coefficient.

Column 2 of Table 3 replicates column 1 for S&P 500 index deletions. As with additions, the coefficients are negative for the first three decades, and statistically significant in the 1990s and 2000s. In the 2010s, the sign switches, although the coefficient is not statistically significant. Again, this suggests that changing characteristics of deletions cannot explain the decline in the index removal effect. Consistent with our results in Section 1.2, the coefficients become statistically insignificant in the last two periods i.e., the deletion effect had disappeared by the 2010s. Turning to the characteristics, past turnover has the expected sign but is statistically insignificant. Like the regression for additions, the size of the deletion matters, and the effect is more than 3× as large as the coefficient in column 1.

The bottom line from Table 3 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.

2.2 Explanation 2: Changes in average liquidity

Another natural explanation for the decline in the index addition effect is an increase in average liquidity. The logic is that if the market has just generally become better at absorbing demand shocks, then when the mechanical buying associated with index changes arrives, prices move less.

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 Jacobson (2014) to compute the percent effective spread. In words, 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.

Figure 4 plots the value-weighted effective spread for all ordinary common shares traded on major exchanges. The blue line represents this quantity computed using the second-based TAQ data, while the red line represents the same quantity for the millisecond-based 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 bottom 100 stocks by market capitalization in the S&P 500.

The bid-ask spread capture 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. Figure 5 shows that, over our sample, implementation shortfall fell significantly less than the average bid-ask spread. Together, Figure 4 and Figure 5 paint a mixed picture.

One can use these aggregate numbers to do a back-of-the-envelope calculation on whether the increase in average liquidity can explain the decline in the index addition effect. As shown in Figure 1, net buying and selling by trackers has increased by a factor of 6-7 (vs. the 10× factor decline in spreads). So, just considering changes in average liquidity based on Figure 4, we might have expected the index inclusion effect to decline slightly, but not by as much as it did. Further, the timing of the spread decline does not synch with the elimination of event returns: most of the decline in average spreads occurred from the mid-1990s to the mid-2000s, while Figure 2 shows that a significant amount of the decline in the addition effect occurred from the mid-2000s to late 2010s. If instead we use the trading costs of institutional investors shown in Figure 5—which is flat – we would have expected an increasing index addition and deletion effect, given the substantial increase in assets tied to the index.

2.3 Explanation 3: Index Migrations

A third explanation is that we have mismeasured the net demand, and that properly measured demand for additions has fallen (with similar results for deletions). A notable type of index change for which this holds is so-called index "migrations". An index change is a migration when it moves from the S&P MidCap index to the S&P 500 or vice versa. An example of this would be Targa Resources (Ticker: TRGP) 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 and SmallCap universe. An example of this is PG&E (Ticker: PCG) which was 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 (Sammon and Shim, 2022).[13] As mid-cap focused funds have grown, so has the magnitude of the negative demand shock, which we would expect to reduce the price impact of a firm being added to the S&P 500. Jointly, these facts imply that migrations should have smaller index inclusion effects than direct additions, and the difference between migrations and non-migrations should be increasing over time.

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 1990, the MidCap changes dataset starts in 1995. We follow a similar procedure to the one described in Section 1.1 to match these observations to CRSP. Figure 6 shows that migrations have become an increasingly large share of additions and deletions. In the mid-1990s, migrations were about 40% of additions and 0% of drops. In recent years, they both make up over 60% of index changes.[14]

[13] The passive ownership industry being overweight mid-cap stocks is not specific to the S&P MidCap universe in particular, but stocks in that part of the firm-size distribution.

[14] The pattern is even more dramatic if we consider all additions rather than our subsample, as migrations made up only 20% of all additions in the mid-1990s (vs. 40% in our sample).

Next, we compare the average returns by year of migrations from the S&P MidCap to direct additions.[15] The bottom left panel of Figure 7 shows that direct adds to the S&P 500 have experienced a decline in the index inclusion effect over the past 25 years. Specifically, for direct additions, the index inclusion effect was 9.6% in the late 90s, 7.5% in the early 2000s, 5.1% in the late 2000s, 1.6% in the early 2010s and 4.1% in the late 2010s and 2020. The large positive return in the last period is driven by Tesla, which as discussed above had a massive return between the announcement and effective date.[16]

The bottom right panel shows that, consistent with the increased size of the offsetting demand shock due to the rise of MidCap funds, there has been a significant decline in the index inclusion effect for migrations. For migrations, the index inclusion effect was 5.8% in the late 1990s, 5.9% in the early 2000s and 1.6% in the late 2000s. By the 2010s, this effect became negative, at -2.6% for both the early and late 2010s.

Interestingly, these mechanisms don't seem to apply equally to deletions. When a firm migrates from the S&P 500 to the MidCap, the mechanical selling by S&P 500 funds should be met by mechanical buying by MidCap funds. So, given the results on migration additions, we would expect that the drops to the MidCap should have had returns which are less negative over time. The top right panel of Figure 7, however, shows mixed evidence on this, as returns to migrations initially increased from 1995-2015, but then decreased thereafter. Further, the top left panel shows that most of the decline (in magnitude) of the index deletion effect came from firms which were dropped to outside the index, where presumably there is no offsetting demand shock. For such firms, the index removal effect was -13.0% in the late 1990s, -16.1% in the early 2000s, -12.4% in the late 2000s, and finally becoming insignificantly different from zero by the late 2010s.

2.4 Explanation 4: Predictability of Index Changes

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[15] We exclude migrations from the S&P SmallCap to the S&P 500 because in our sample, few firms migrate between the large and small cap indices directly.

[16] 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. So, the total cumulative market adjusted 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, an article in Bloomberg describes how a 20-person team at Goldman Sachs earned $700 million a year in profit betting on index additions and deletions across a variety of indexes. 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 reversion 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 go up in value are more likely to be added to the index in the first place.

We start by looking at cumulative pre-addition returns. To this end, we calculate the cumulative market-adjusted returns starting 100 trading days before the announcement of the index change to 10 trading days after the announcement. Figure 8 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 market-adjusted return up to the day before the announcement was 6.4% in the 1990s, 9.1% in the 2000s and 11.6% in the 2010s. Then, the cumulative return up to the day after the announcement was 12.1% in the 1990s, 13.8% in the 2000s and 14.7% in the 2010s. Finally, by 11 trading days after the announcement, in every decade the cumulative returns are between 13 and 14%. So, even though the total distance traveled is similar, in more recent years, most of this occurred before the announcement while in past years most of it happened before. As can be seen in the lower panel, these same patterns are mirrored for drops.

As we noted, one issue with Figure 8 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.

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 10, we plot the average rank of firms that end up getting added, as well as the 25th and 75th percentile of these ranks.[17] Of course, this is an imperfect ranking system as it does not account for (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.[18] Panel A shows that over time, it seems as though S&P has moved to picking larger firms. The picking of larger firms also seems to have become more consistent, as the interquartile range has declined. This, however, does not mean it's easy to predict additions using size alone, 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 (at least on the size dimension).

One concern with the results in Panel A is that the number of publicly listed firms has been declining (Doidge, Karolyi and Stulz, 2017). This trend could mechanically increase the rank of added firms if S&P always chose firms in the same part of the firm-size distribution. To address this concern, in Panel B, we plot

[17] 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.

[18] There are huge firms, such as publicly-listed private equity firms, that do not meet S&P criteria in spite of their size.

the percentile rank of added firms. The pattern is similar to Panel A, suggesting that the decline in the universe of public firms does not explain this result.

A final place to look is post-index-change returns i.e., to check for the reversion we would expect in a world with downward sloping demand curves. Figure 9 plots the cumulative market-adjusted returns from t=-1 before the announcement to 100 days after the index inclusion. In the 1990s and 2000s, there was a significant reversion in the month following the index change. Specifically, in the early 1990s, the cumulative market-adjusted return peaks 6 days after the announcement at 7.5%. It falls thereafter to 6% by 15 trading days and stays roughly there for the next 85 trading days. In the 2000s, the cumulative return peaks at 6 trading days after the announcement at 4.1%, reverting to 2% by 29 trading days and roughly staying there for the next 71 trading days. Interestingly, there is very little reversion in the 2010s. The return peaks at 1.1% 1 trading day after the announcement and then stays near zero thereafter. As with the post-addition returns, these patterns are mirrored for drops as well.

2.5 Explanation 5: Event-specific liquidity

A fifth class of explanation is to simply take the facts from Section I at face value, interpreting them as prices becoming more elastic for S&P 500 index additions and deletions. Or, put differently, that the market is more efficient today at accommodating the required changes in ownership associated with index addition and deletion. To the extent that the other three explanations we have considered cannot fully account for the facts, it *must* be an increase in market efficiency playing at least some role.

How and why, then, did the market become more efficient in this context? One notable feature of index changes is an increased density of trading on the effective date itself. This is built on 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, 2022). To quantify this, and following Chinco and Sammon (2022) for each addition or deletion, we compute the total trading volume in a +/- 22 trading-day window around the event. Then, we compute the share of volume on each day and take an average across all firms each in a set of 5-year blocks. In Panel A of Figure 11, we show that for additions in the early 1990s, about 15% of trading around the index changes happened on the effective date itself, while now it is closer to 30%. Panel B of Figure 11 shows a similar pattern for deletions.

Another underappreciated feature of index additions is that while a large, dedicated group of mutual funds and ETFs must buy, on average, institutional ownership changes very little around these events. Put differently, other institutions provide liquidity for index trackers. A possible mechanism is that intermediaries (e.g., investment banks) contact managers of mid-cap focused equity funds and tell them to arrive at the closing auction and provide liquidity to the index funds. 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.

In Table 4, we compare 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. This suggests that other institutions have stepped up to meet the buying and selling pressure from S&P 500 funds.

Finally, it's possible that price impact has gone down over time because index-tracking trades have become more transparent. For example, ETFs publish the baskets they are willing to accept every day. So, as uninformed demand has become easier to identify, it's possible that market makers endogenously lower price impact to accommodate this uninformed demand.

2.6 Discussion

Overall, the findings suggest the following possible sequence of events. In the 1980s, index changes were unanticipated, but index funds were small, so the addition effect was 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 inclusions.

The index provider, S&P also adapted to mitigate market froth associated with index changes. In particular, the S&P 500 grew to rely more on index migrations, which helped to reduce overall price impact. 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. In this sense, the decline of the index effect is much like the evidence for other anomalies, that they decline once they are well recognized by the market (McLean and Pontiff 2016).

3. 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 five explanations why this happened. To sum up, our assessment is that the declining index effect is driven by primarily two factors: an increase in migrations over time from the S&P MidCap Index, and an overall increase in the market's ability to provide liquidity to index changes. We cannot rule out that a third factor, increased predictability of index changes, played some role. Overall then, 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.

Our findings raise the question of whether the inclusion and deletion anomalies in indexes outside of the S&P 500 will similarly disappear over time. As important as the S&P 500 is, it is but one of many indexes tracked by global investors, including the Russell and MSCI global indexes as well as many nationally important indexes such as the TOPIX and the Nikkei 225. For example, Chinco and Sammon (2022) find that over the past 10 years, the Russell 1000 and 2000 inclusion and reconstitution effects (Madhavan, 2003) have declined. Subsequent work may shed light on how the channels we have discussed apply in these different settings and at what speed markets adapt to eliminate anomalies.

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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. Equal weighted average among events by year. Red line represents a LOWESS filter (bandwidth = 0.8).

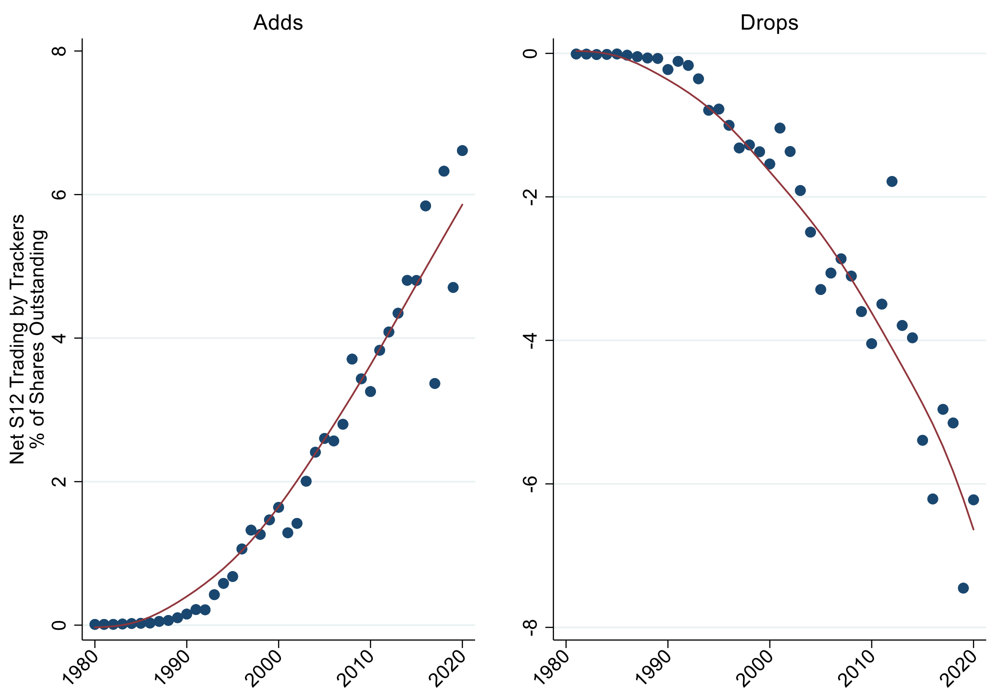
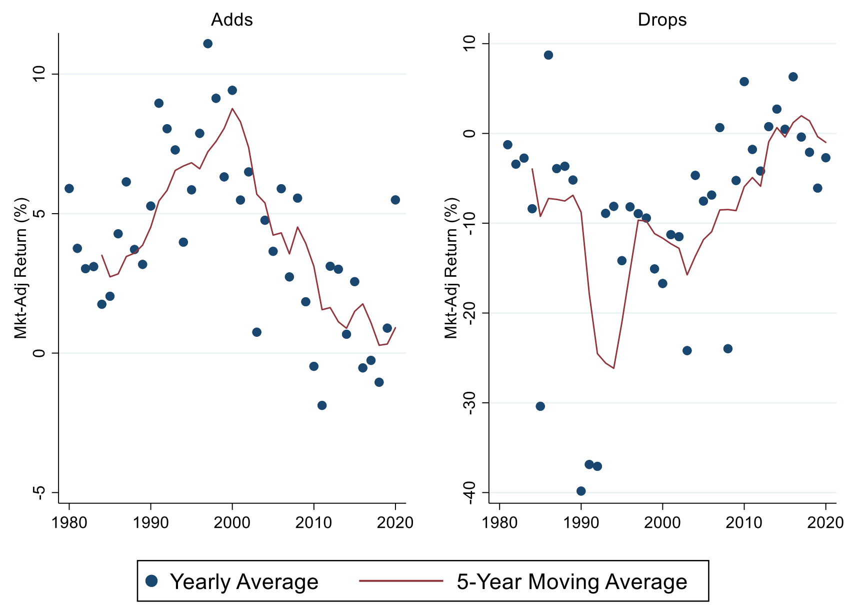


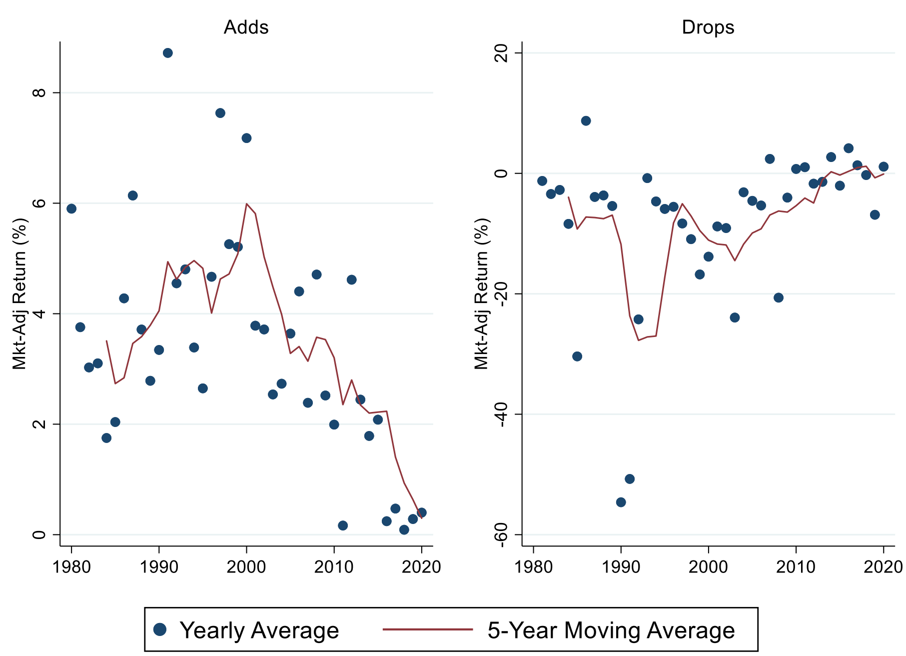
Figure 2. Average index effect by year.

For each event, we compute the cumulative market-adjusted return over the period of interest. Blue dots represent the average for adds and drops each year. The red line represents the 5-year moving average of this quantity, starting 5 years into our sample.

Panel A. Total effect: returns from the day before the announcement to the day after the implementation.



Panel B. Announcement effect: return from the day before to the day after the announcement.



Panel C. Implementation effect: return from the day before to the day after the effective date.

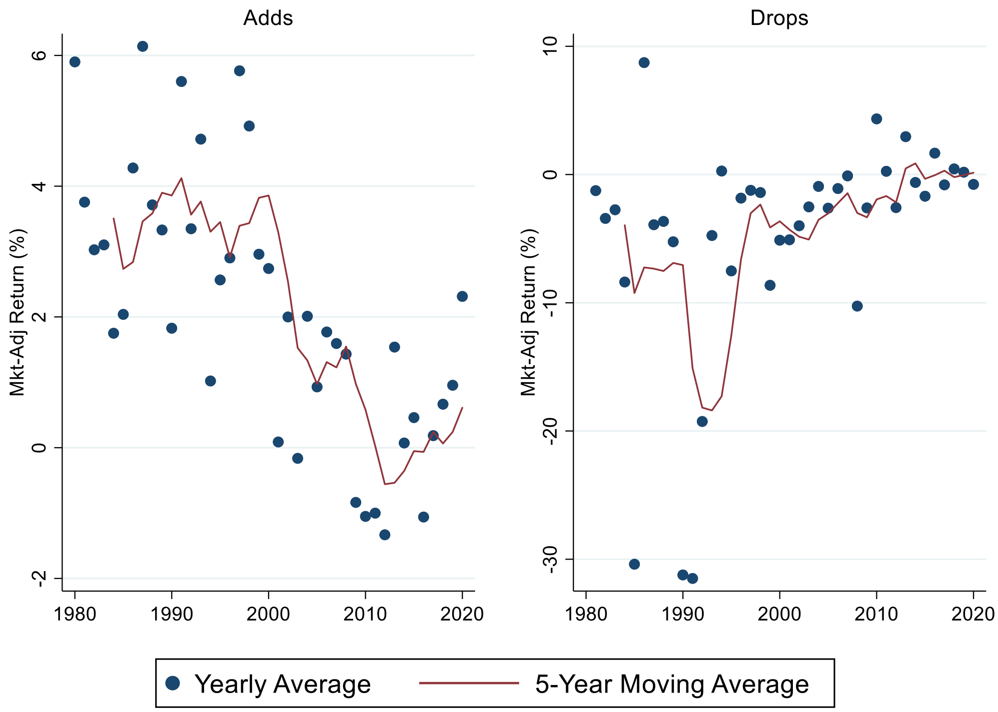


Figure 3. Forced buying and selling, and the index effect.

Each point represents an individual addition or deletion event. Mechanical buying is 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). Y-axis represents the total inclusion effect return i.e., the cumulative return from the day before the announcement to the day after the implementation.

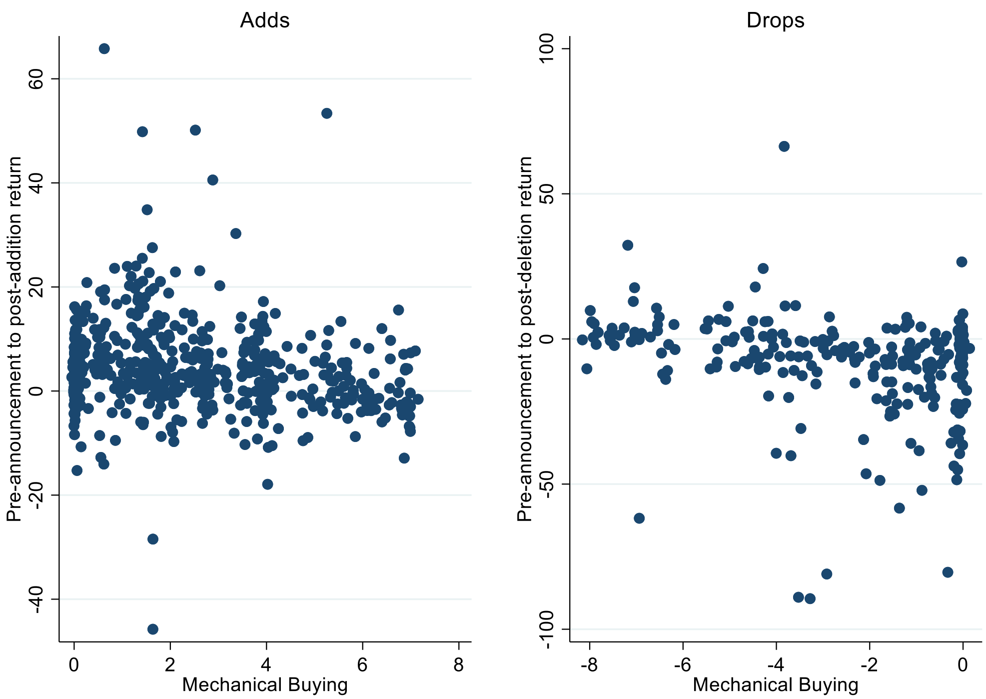


Figure 4 Value-weighted average effective bid-ask spreads.

Percentage effective spread computed from TAQ data using the method in Holden and Jacobson (2014). Weights are proportional to each firm's one-month lagged market capitalization. The blue dots represent estimates from the second-based TAQ data, while the red dots represent estimates from the millisecond-based TAQ data.

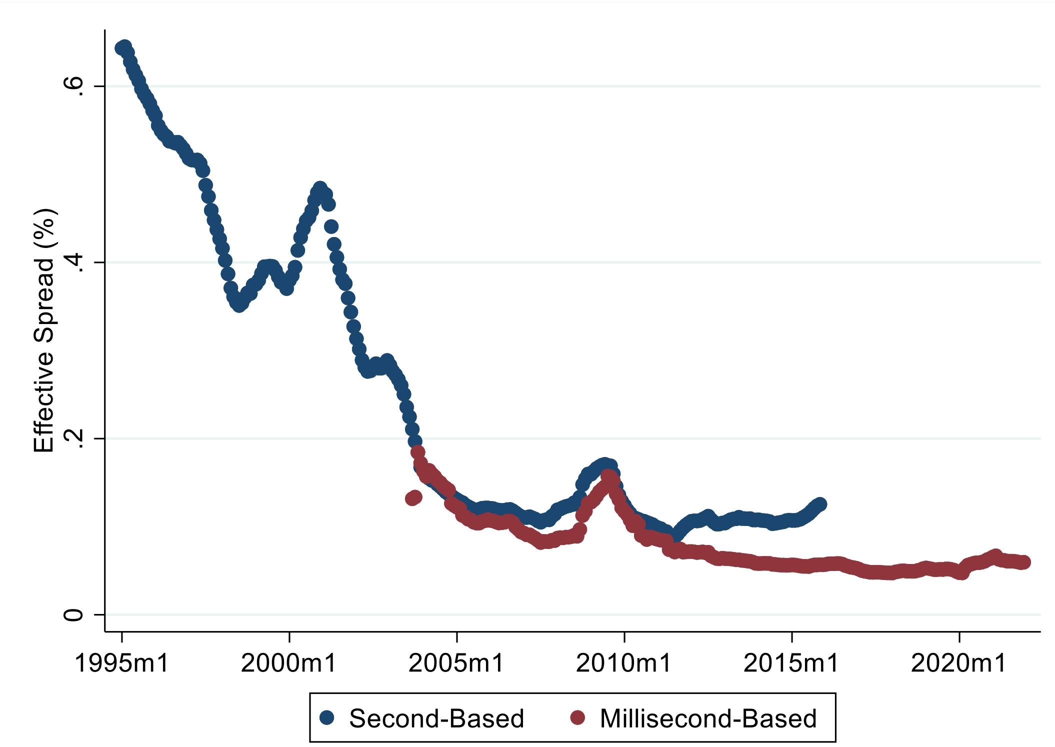


Figure 5. Implementation shortfall, midcap stocks

Implementation shortfall 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.

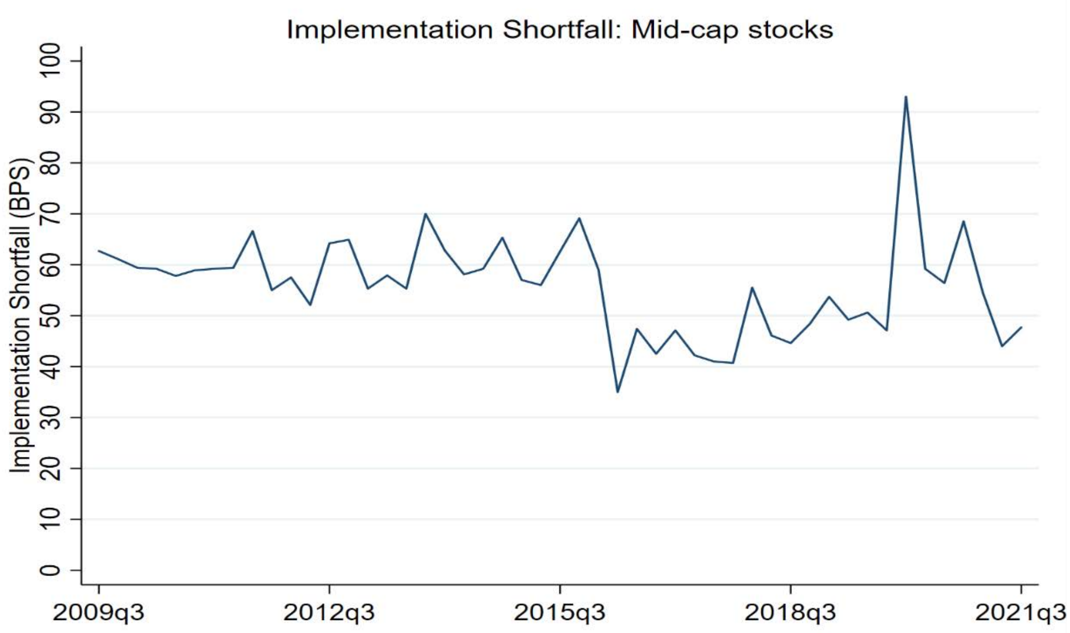


Figure 6. Migrations as a fraction of S&P 500 additions and deletions.

Each year, we identify migration additions as firms which are simultaneously added to the S&P 500 and dropped from the S&P MidCap. We identify migration deletions as firms which are simultaneously dropped from the S&P 500 and added to the S&P MidCap. Then we compute the fraction of additions and deletions in our sample which are migrations each year. Green and blue lines represent LOWESS filters (bandwidth=0.8).

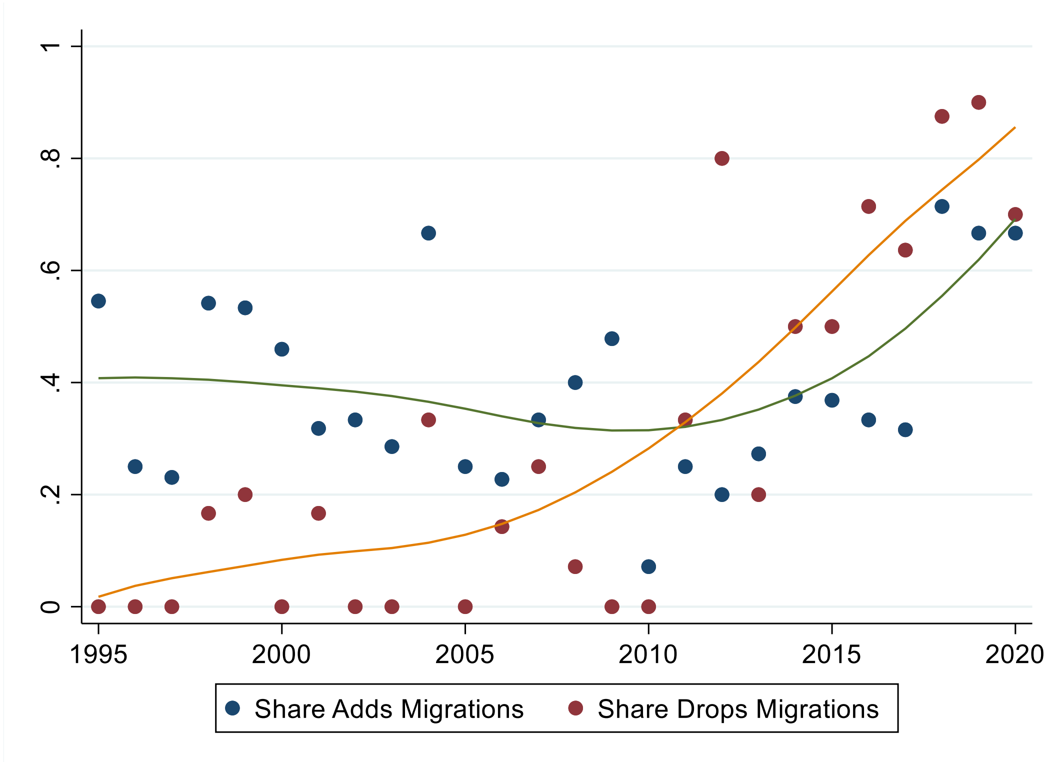


Figure 7. Comparing addition and deletion returns across index migrations and "direct adds" or "direct deletions"

For each event, we compute the market-adjusted return from the day before the announcement to the day after the implementation. Blue dots represent the average of this quantity each year. The red line represents a LOWESS filter (bandwidth=0.8).

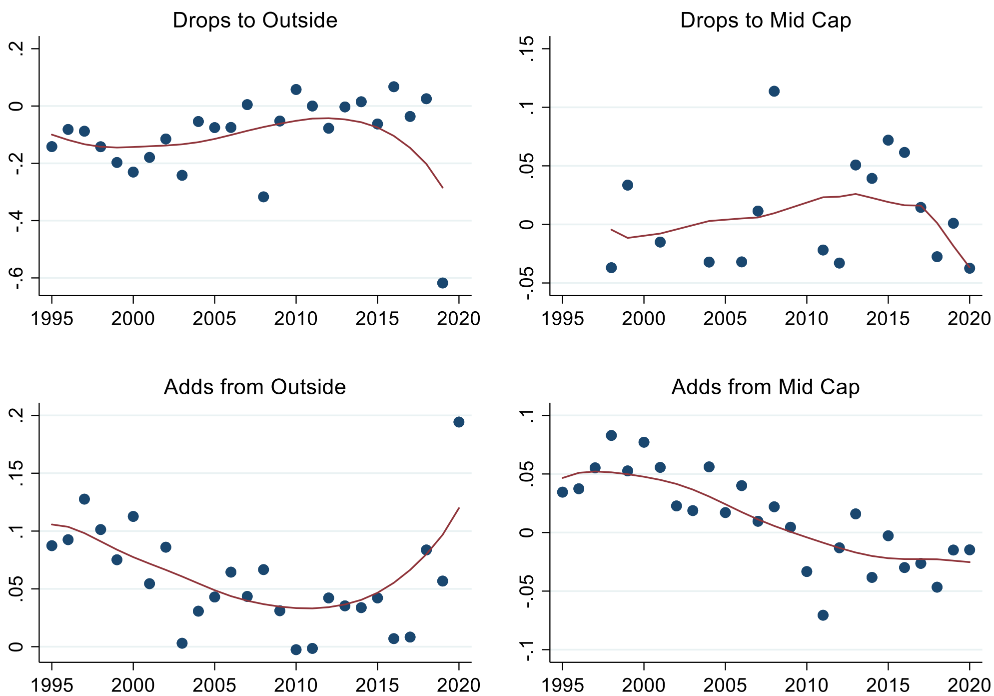
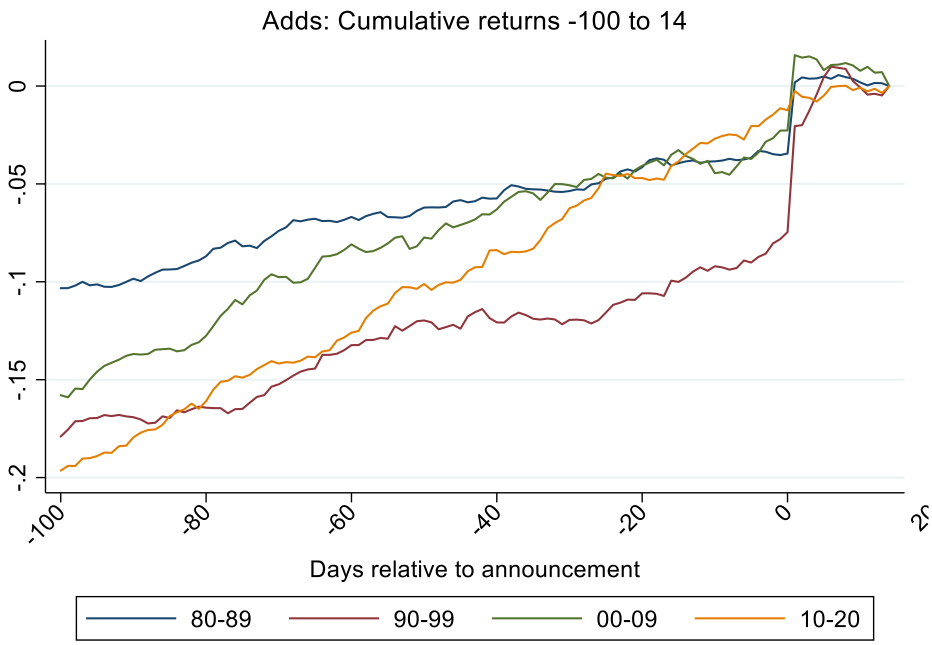


Figure 8. Cumulative pre-addition and pre-deletion market-adjusted returns.

Average cumulative returns in event time, pooled for 1980-1989, 1990-1999, 2000-2009, and 2010-2020. Normalized to 0 ten trading days after the announcement.



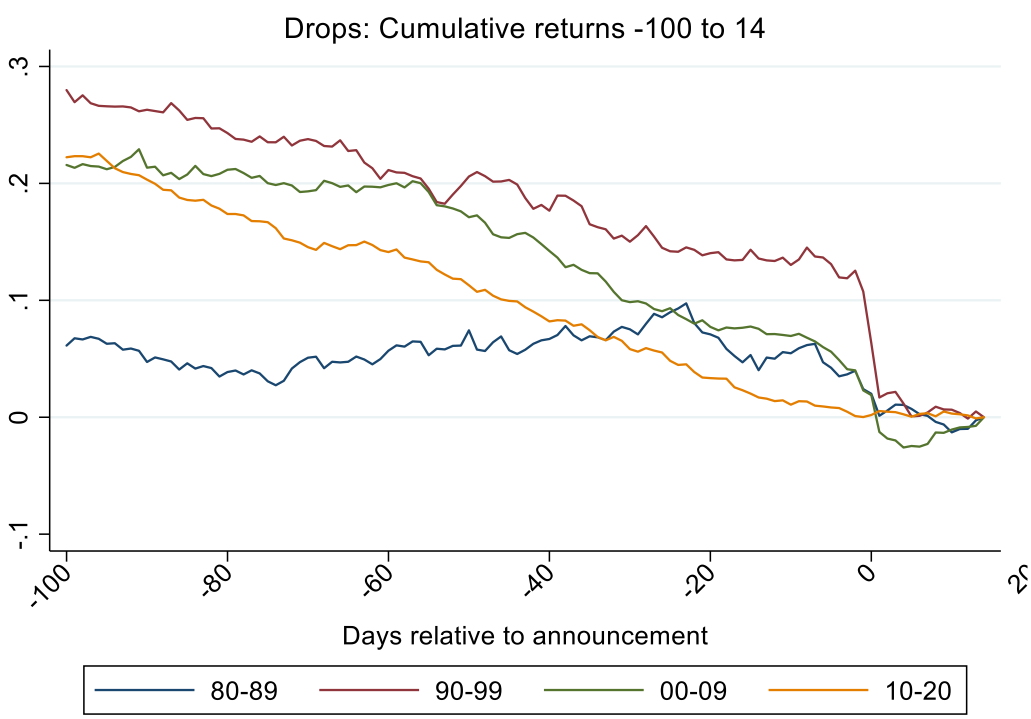
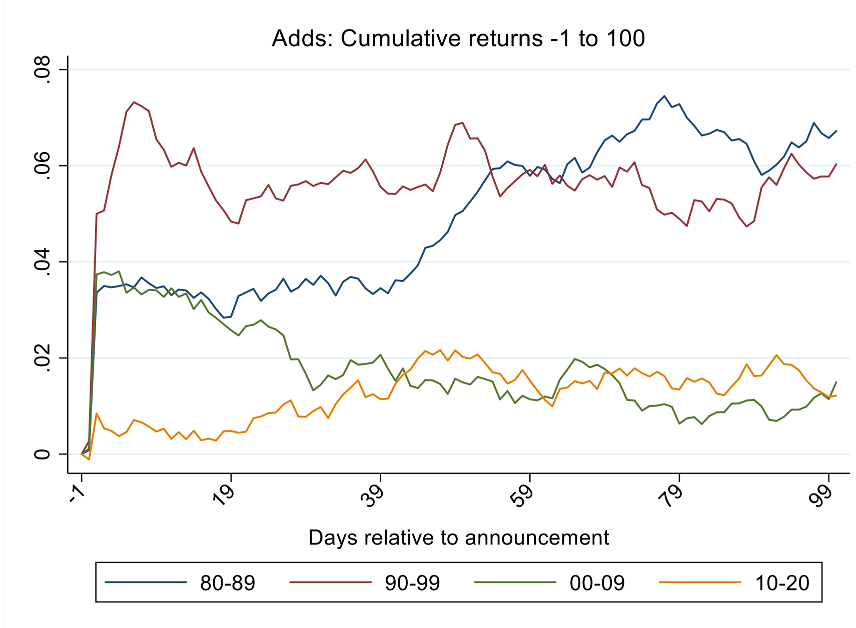


Figure 9. Cumulative post-addition and post-deletion market-adjusted returns.

Average cumulative returns in event time, pooled for 1980-1989, 1990-1999, 2000-2009, and 2010-2020. Normalized to zero the day before the index addition or deletion.



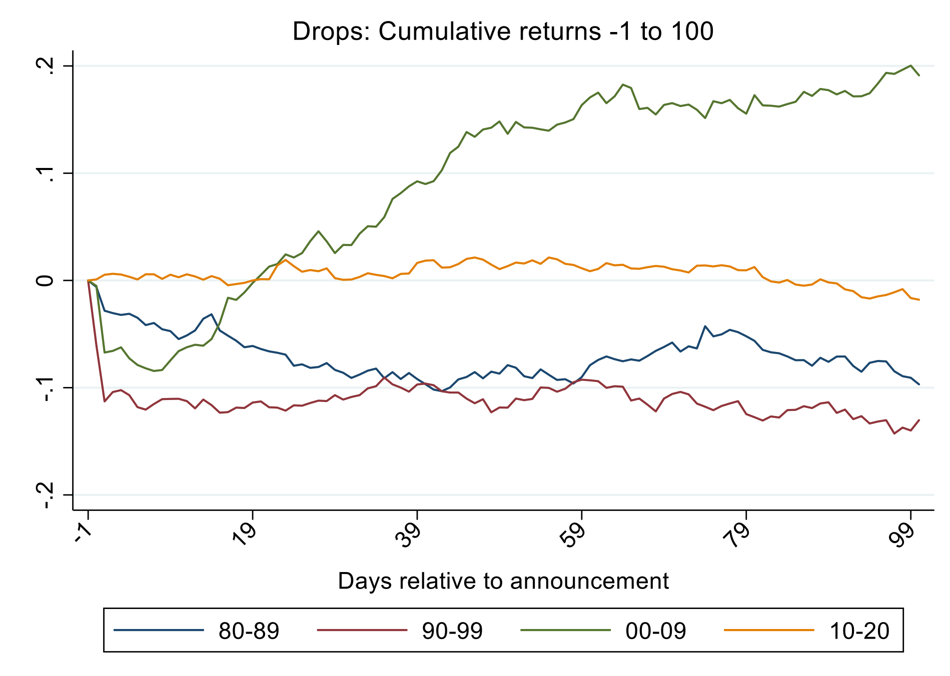
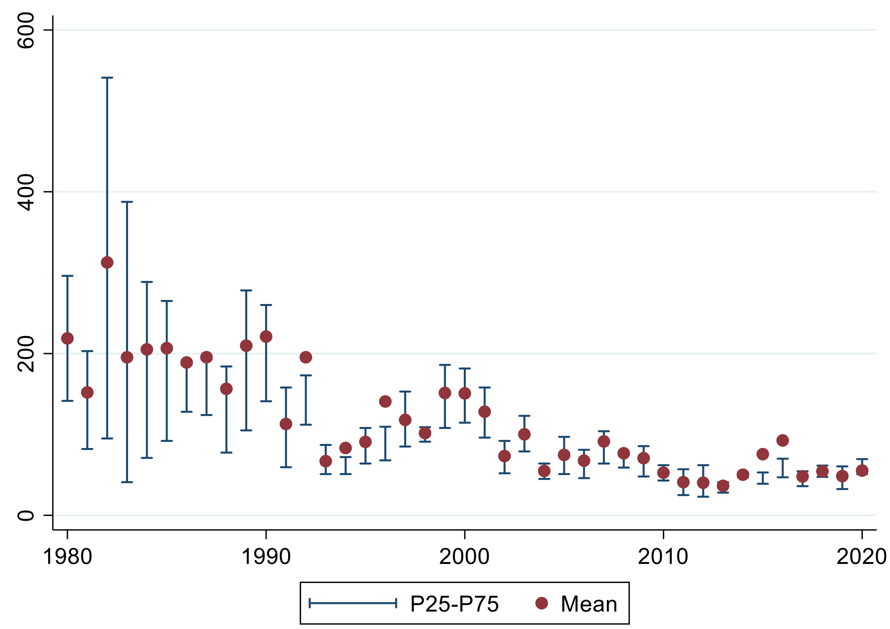


Figure 10. Rank of additions among stocks outside the index by year.

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. Panel A shows raw ranks; Panel B shows percentile ranks i.e., rank divided by the total number of ordinary common shares traded on major exchanges not in the S&P 500.

Panel A. Ranks



Panel B. Percentile Ranks

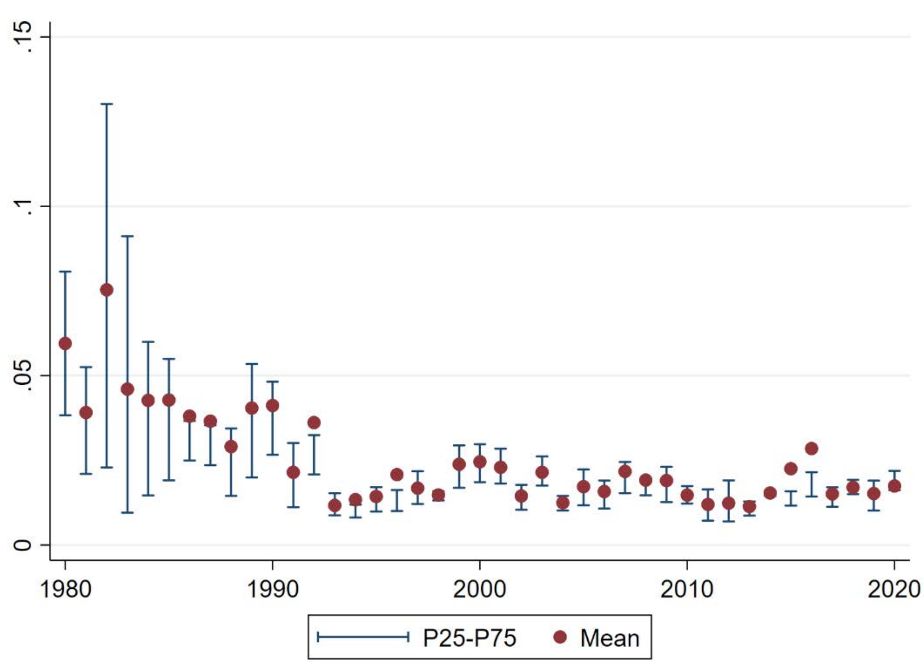
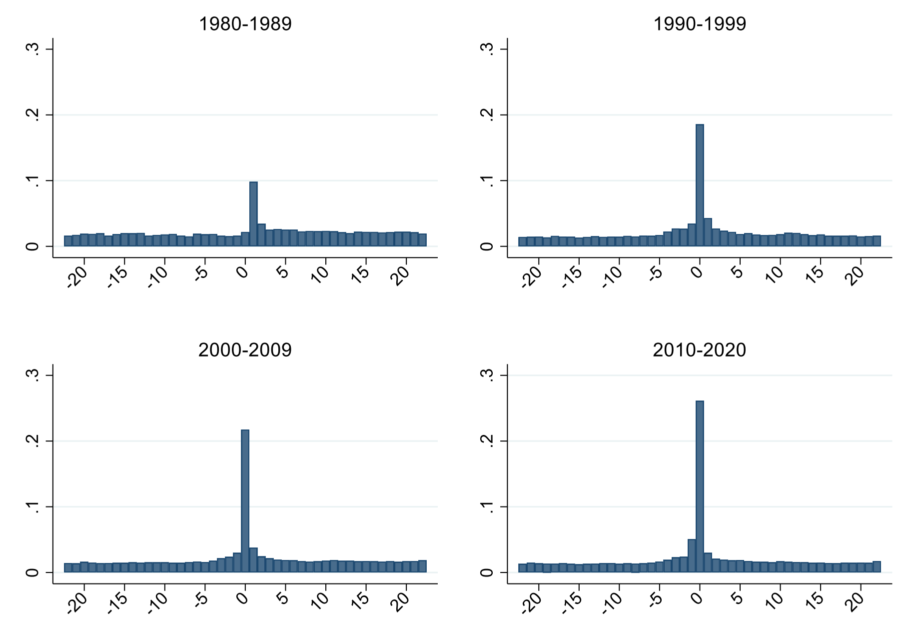


Figure 11. Share of volume on days -22 to +22 around the effective index change.

For each addition or deletion, we compute the total trading volume in a +/- 22 trading-day window around the event. Then, we compute the share of volume on each day and take an average across all firms each in each 10-year block.

Panel A. Additions



Panel B. Deletions

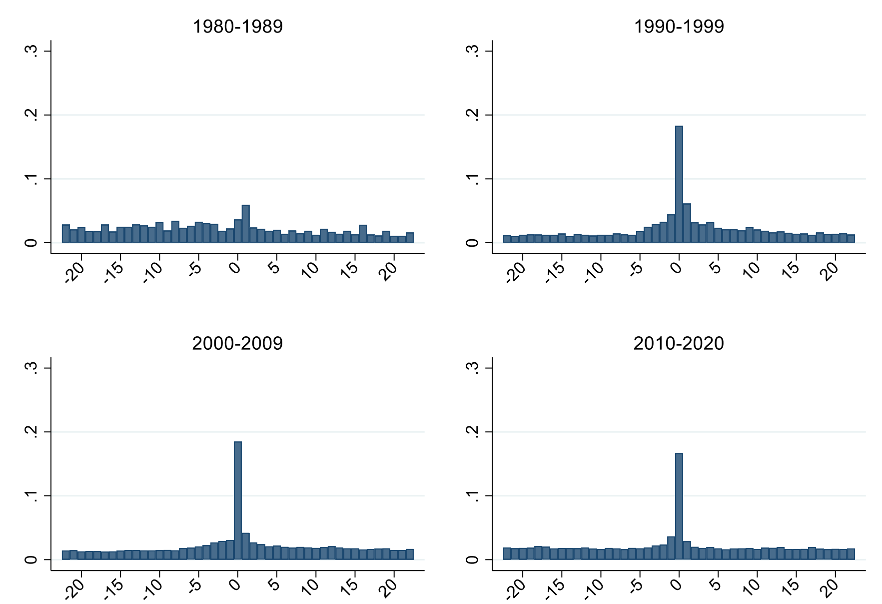


Table 1. Addition and Deletion Returns by year.

Announcement returns (Ann.) are the returns from the day before to the day after the announcement. Effective returns (Eff.) are the returns from the day before to the day after the index change became effective. Total returns are the 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 the median for the total return. All returns are market-adjusted.

	Additions					Deletions				
		Mean			Median		Mean			Median
Year	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**
1980	5	5.90%	5.90%	5.90%	3.84%	0	-	-	-	-
1981	15	3.76%	3.76%	3.76%	3.53%	2	-1.25%	-1.25%	-1.25%	-1.25%
1982	22	3.03%	3.03%	3.03%	2.44%	4	-3.42%	-3.42%	-3.42%	-3.82%
1983	8	3.10%	3.10%	3.10%	2.51%	6	-2.75%	-2.75%	-2.75%	-2.71%
1984	28	1.75%	1.75%	1.75%	1.64%	3	-8.38%	-8.38%	-8.38%	-6.11%
1985	26	2.04%	2.04%	2.04%	1.70%	2	-30.39%	-30.39%	-30.39%	-30.39%
1986	23	4.28%	4.28%	4.28%	3.69%	3	8.73%	8.73%	8.73%	2.05%
1987	21	6.14%	6.14%	6.14%	6.98%	2	-3.91%	-3.91%	-3.91%	-3.91%
1988	20	3.71%	3.71%	3.71%	5.02%	5	-3.66%	-3.66%	-3.66%	0.11%
1989	28	2.79%	3.33%	3.18%	3.36%	12	-5.41%	-5.24%	-5.19%	0.30%
1990	7	3.34%	1.83%	5.27%	6.92%	2	-54.61%	-31.22%	-39.83%	-39.83%
1991	8	8.72%	5.60%	8.96%	8.03%	4	-50.74%	-31.50%	-36.87%	-38.19%
1992	5	4.55%	3.35%	8.04%	4.55%	5	-24.24%	-19.26%	-37.07%	-25.58%
1993	7	4.80%	4.72%	7.29%	8.36%	3	-0.79%	-4.76%	-8.90%	-3.54%
1994	7	3.39%	1.02%	3.98%	5.69%	6	-4.66%	0.27%	-8.12%	-8.47%
1995	11	2.65%	2.57%	5.85%	6.75%	10	-5.91%	-7.51%	-14.17%	-13.11%
1996	16	4.67%	2.90%	7.88%	5.10%	7	-5.55%	-1.84%	-8.17%	-5.68%
1997	13	7.63%	5.77%	11.09%	10.91%	3	-8.32%	-1.23%	-8.93%	-8.88%
1998	24	5.26%	4.92%	9.13%	7.85%	6	-10.92%	-1.41%	-9.42%	-8.11%
1999	30	5.21%	2.96%	6.32%	7.34%	5	-16.78%	-8.64%	-15.09%	-4.50%
2000	37	7.18%	2.74%	9.42%	5.16%	17	-13.83%	-5.12%	-16.71%	-15.16%

Table 1. [Continued]

	Additions					Deletions				
		Mean			Median		Mean			Median
Year	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**	**# Obs**	**Ann. Return**	**Eff. Return**	**Total Return**	**Total Return**
2001	22	3.78%	0.09%	5.49%	1.64%	6	-8.81%	-5.09%	-11.27%	-7.02%
2002	15	3.72%	2.00%	6.50%	4.17%	11	-9.08%	-3.99%	-11.50%	-7.35%
2003	7	2.54%	-0.16%	0.75%	1.61%	3	-23.94%	-2.52%	-24.18%	-21.28%
2004	12	2.73%	2.01%	4.76%	3.62%	6	-3.14%	-0.92%	-4.67%	-5.14%
2005	12	3.64%	0.93%	3.65%	3.24%	2	-4.56%	-2.62%	-7.53%	-7.53%
2006	22	4.40%	1.77%	5.89%	6.08%	7	-5.33%	-1.09%	-6.86%	-6.06%
2007	30	2.39%	1.59%	2.73%	2.41%	4	2.41%	-0.10%	0.65%	0.21%
2008	30	4.71%	1.43%	5.56%	5.92%	14	-20.64%	-10.26%	-23.98%	-16.40%
2009	23	2.52%	-0.84%	1.84%	1.16%	16	-4.02%	-2.60%	-5.24%	-4.01%
2010	14	1.99%	-1.05%	-0.47%	0.22%	3	0.74%	4.34%	5.77%	-0.68%
2011	8	0.17%	-1.00%	-1.87%	-0.76%	9	1.03%	0.25%	-1.78%	-1.24%
2012	5	4.61%	-1.33%	3.11%	2.79%	5	-1.71%	-2.58%	-4.19%	-7.76%
2013	11	2.45%	1.54%	3.01%	2.99%	10	-1.40%	2.95%	0.76%	0.15%
2014	8	1.79%	0.07%	0.68%	0.08%	8	2.71%	-0.62%	2.71%	3.50%
2015	19	2.08%	0.46%	2.56%	1.98%	6	-2.04%	-1.69%	0.47%	0.68%
2016	21	0.24%	-1.06%	-0.53%	-1.02%	7	4.18%	1.67%	6.31%	2.84%
2017	19	0.47%	0.18%	-0.26%	-0.57%	11	1.35%	-0.80%	-0.40%	0.95%
2018	21	0.09%	0.67%	-1.04%	-2.61%	8	-0.28%	0.44%	-2.09%	1.92%
2019	12	0.28%	0.95%	0.90%	-0.88%	10	-6.87%	0.18%	-6.09%	0.11%
2020	12	0.40%	2.31%	5.49%	0.64%	10	1.11%	-0.77%	-2.70%	-3.33%

Table 2. Addition and Deletion Returns by decade

In each 10-year period, we run a regression of the individual total, announcement and implementation return on a constant term. Announcement returns are the returns from the day before to the day after the announcement. Effective returns are the returns from the day before to the day after the index change became effective. Total returns are the returns from the day before the announcement to the day after the index change became effective. The last column shows the difference between the 2010-2020 period and the 2000-2009 period. Robust standard errors in parenthesis.

Panel A: Additions

	All	**1980-1989**	**1990-1999**	**2000-2009**	**2010-2020**	**(2010-2020) - (2000-2009)**
Total	0.0417***	0.0342***	0.0759***	0.0521***	0.00799	-0.044***
	(0.003)	(0.003)	(0.008)	(0.007)	(0.006)	(0.009)
Announcement	0.0342***	0.0336***	0.0515***	0.0413***	0.0105***	-0.031***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
Effective	0.0213***	0.0344***	0.0368***	0.0132***	0.00209	-0.011**
	(0.002)	(0.003)	(0.005)	(0.004)	(0.002)	(0.005)
Observations	684	196	128	210	150	N/A

Panel B: Deletions

	All	**1980-1989**	**1990-1999**	**2000-2009**	**2010-2020**	**(2010-2020) - (2000-2009)**
Total	-0.0813***	-0.0464**	-0.166***	-0.123***	-0.00603	0.117***
	(0.011)	(0.018)	(0.023)	(0.023)	(0.011)	(0.026)
Announcement	-0.0687***	-0.0471**	-0.144***	-0.101***	-0.002	0.099***
	(0.010)	(0.018)	(0.029)	(0.021)	(0.009)	(0.023)
Effective	-0.0372***	-0.0465**	-0.0864***	-0.0434**	0.002	0.045**
	(0.008)	(0.018)	(0.021)	(0.019)	(0.006)	(0.019)
Observations	263	39	51	86	87	N/A

Table 3. Abnormal returns, controlling for characteristics

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

$$Total\ Return_{it} = b_1 turnover_{i,t-1} + b_2\ size_{i,t-1} + b_3 volatility_{i,(t-12,t-1)} + \sum_{k=1}^{4} \gamma_k 1_{era=k} + e_{it}$$

Where $Total\ Return_{it}$ is the cumulative return from the day before the announcement to the day after the implementation. $turnover_{i,t-1}$ 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. $volatility_{i,(t-12,t-1)}$ is a 12-month moving average of the sum of daily squared percentage market-adjusted stock returns computed each month. $1_{era=k}$ are dummy variables for 10-year periods.

	Additions	Deletions
	(1)	(2)
Turnover t-1	-0.0292	-1.051
	(0.44)	(1.11)
% of S&P Cap.	17.19***	25.38**
	(4.29)	(10.82)
Stock Volatility t-12 to t-1	0.206***	-0.210**
	(0.08)	(0.10)
1980-1989	1.022*	-2.62
	(0.59)	(2.53)
1990-1999	4.329***	-14.00***
	(1.07)	(2.42)
2000-2009	1.550**	-7.448***
	(0.74)	(1.84)
2010-2020	-1.851***	3.059
	(0.61)	(2.61)
Observations	678	263
R-squared	0.35	0.368

Table 4. Net buying and selling by trackers and institutional investors.

Net buying and selling by trackers are defined as in Figure 1. Net buying and selling by institutions (Insts.) are 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. 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.

	Additions		Deletions	
Year	Index Trackers Only	All Institutions	Index Trackers Only	All Institutions
1990	0.15%	0.54%	-0.23%	-23.99%
1991	0.22%	1.58%	-0.12%	-5.76%
1992	0.26%	0.97%	-0.16%	-4.22%
1993	0.49%	1.68%	-0.41%	-1.18%
1994	0.56%	0.77%	-0.66%	-3.97%
1995	0.66%	3.23%	-0.69%	-3.02%
1996	1.10%	0.27%	-1.00%	-1.56%
1997	1.35%	0.33%	-1.28%	1.88%
1998	1.46%	0.87%	-1.36%	-1.74%
1999	1.59%	0.28%	-1.45%	-0.42%
2000	1.60%	1.36%	-1.55%	-3.47%
2001	1.08%	0.42%	-0.91%	1.81%
2002	1.34%	-0.06%	-1.15%	-2.00%
2003	2.15%	-1.09%	-2.01%	3.69%
2004	2.42%	0.93%	-2.33%	0.52%
2005	2.70%	-0.20%	-3.29%	-2.01%
2006	2.63%	0.36%	-3.00%	-3.20%
2007	2.80%	0.45%	-2.88%	-1.94%
2008	3.84%	1.46%	-3.50%	-7.35%
2009	3.75%	0.42%	-4.09%	-2.82%
2010	3.84%	0.61%	-4.28%	3.56%
2011	4.11%	0.30%	-4.51%	-0.25%
2012	4.28%	0.73%	0.00%	-0.07%
2013	4.68%	1.86%	-4.78%	0.45%
2014	4.97%	2.49%	-5.13%	2.64%
2015	5.33%	1.11%	-6.32%	-4.16%
2016	5.97%	0.59%	-6.55%	-2.97%
2017	5.18%	0.47%	-6.88%	0.32%
2018	6.81%	0.61%	-5.78%	-1.62%
2019	6.04%	0.36%	-7.57%	-6.40%
2020	6.85%	-0.66%	-7.47%	-0.75%
Average	2.91%	0.74%	-2.95%	-2.26%

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.

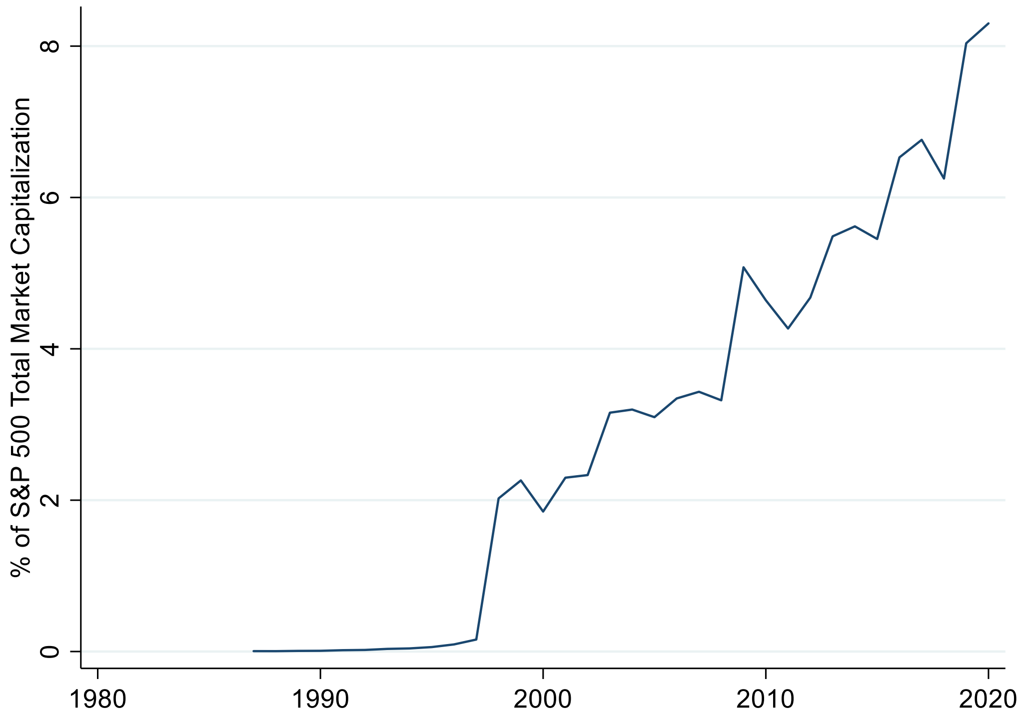


Table A1. Sample selection

We report the annual number of S&P 500 index additions and deletions 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 acquirers 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.

Year	Total Drops	Drops Sample	% Included	Total Adds	Adds Sample	% Included
1980	-	-	-	11	5	45%
1981	3	2	67%	21	15	71%
1982	13	4	31%	27	22	81%
1983	11	6	55%	11	8	73%
1984	12	3	25%	30	28	93%
1985	11	2	18%	28	26	93%
1986	16	3	19%	28	23	82%
1987	13	2	15%	25	21	84%
1988	22	5	23%	25	20	80%
1989	27	12	44%	29	28	97%
1990	12	2	17%	12	7	58%
1991	12	4	33%	12	8	67%
1992	7	5	71%	7	5	71%
1993	10	3	30%	11	7	64%
1994	17	6	35%	17	7	41%
1995	29	10	34%	28	11	39%
1996	22	7	32%	22	16	73%
1997	26	3	12%	26	13	50%
1998	40	6	15%	40	24	60%
1999	41	5	12%	39	30	77%
2000	55	17	31%	56	37	66%
2001	30	6	20%	30	22	73%
2002	23	11	48%	23	15	65%
2003	8	3	38%	9	7	78%
2004	19	6	32%	18	12	67%
2005	18	2	11%	17	12	71%
2006	30	7	23%	30	22	73%
2007	38	4	11%	38	30	79%
2008	37	14	38%	37	30	81%
2009	26	16	62%	26	23	88%
2010	16	3	19%	16	14	88%
2011	20	9	45%	20	8	40%
2012	17	5	29%	17	5	29%
2013	19	10	53%	19	11	58%
2014	14	8	57%	16	8	50%
2015	24	6	25%	27	19	70%
2016	28	7	25%	28	21	75%
2017	27	11	41%	26	19	73%
2018	23	8	35%	24	21	88%
2019	21	10	48%	21	12	57%
2020	16	10	63%	16	12	75%
Average	23	7	34%	23	16	66%

Table A2. Sensitivity of 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. 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 announcement or implementation. Announcement returns (Ann.) are the returns from the day before to the day after the announcement. Effective returns (Eff.) are the returns from the day before to the day after the index change became effective. Total returns are the returns from the day before the announcement to the day after the index change became effective. All returns are market-adjusted.

	Adds								Drops							
	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	7	3.34%	1.83%	5.27%	12	1.98%	1.56%	3.58%	2	-54.61%	-31.22%	-39.83%	12	-7.55%	-3.86%	-4.84%
1991	8	8.72%	5.60%	8.96%	12	5.66%	5.66%	7.07%	4	-50.74%	-31.50%	-36.87%	12	-16.17%	-11.26%	-11.56%
1992	5	4.55%	3.35%	8.04%	7	3.24%	2.04%	4.82%	5	-24.24%	-19.26%	-37.07%	7	-16.30%	-12.88%	-25.61%
1993	7	4.80%	4.72%	7.29%	11	4.41%	2.94%	5.21%	3	-0.79%	-4.76%	-8.90%	10	0.92%	-1.60%	-2.26%
1994	7	3.39%	1.02%	3.98%	17	1.92%	0.64%	3.14%	6	-4.66%	0.27%	-8.12%	17	-1.41%	0.77%	-1.97%
1995	11	2.65%	2.57%	5.85%	28	3.30%	2.34%	4.58%	10	-5.91%	-7.51%	-14.17%	29	-2.21%	-2.18%	-4.80%
1996	16	4.67%	2.90%	7.88%	22	4.39%	2.25%	6.60%	7	-5.55%	-1.84%	-8.17%	22	-2.40%	-0.15%	-2.09%
1997	13	7.63%	5.77%	11.09%	26	5.87%	3.99%	7.40%	3	-8.32%	-1.23%	-8.93%	26	-0.49%	-0.03%	-0.66%
1998	24	5.26%	4.92%	9.13%	40	4.83%	2.46%	6.54%	6	-10.92%	-1.41%	-9.42%	40	-1.01%	-1.08%	-1.07%
1999	30	5.21%	2.96%	6.32%	39	5.01%	3.31%	7.47%	5	-16.78%	-8.64%	-15.09%	41	-0.91%	-1.14%	-0.61%
2000	37	7.18%	2.74%	9.42%	56	5.90%	1.94%	8.75%	17	-13.83%	-5.12%	-16.71%	55	-3.83%	-1.96%	-4.94%
2001	22	3.78%	0.09%	5.49%	30	2.74%	-0.08%	3.77%	6	-8.81%	-5.09%	-11.27%	30	-7.01%	-2.43%	-6.02%
2002	15	3.72%	2.00%	6.50%	23	3.82%	1.65%	5.37%	11	-9.08%	-3.99%	-11.50%	23	-9.73%	-5.79%	-10.76%
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%	18	1.24%	1.09%	3.24%	6	-3.14%	-0.92%	-4.67%	19	-0.20%	-0.52%	-0.30%
2005	12	3.64%	0.93%	3.65%	17	3.02%	1.23%	3.69%	2	-4.56%	-2.62%	-7.53%	18	-8.38%	-8.73%	-11.06%

	Adds								Drops							
	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
2006	22	4.40%	1.77%	5.89%	30	3.94%	0.56%	3.80%	7	-5.33%	-1.09%	-6.86%	30	-2.00%	-2.22%	-3.70%
2007	30	2.39%	1.59%	2.73%	38	2.11%	0.90%	2.04%	4	2.41%	-0.10%	0.65%	38	0.30%	0.59%	0.85%
2008	30	4.71%	1.43%	5.56%	37	4.41%	1.92%	5.51%	14	-20.64%	-10.26%	-23.98%	37	-9.77%	-6.58%	-11.58%
2009	23	2.52%	-0.84%	1.84%	26	2.96%	-0.94%	1.69%	16	-4.02%	-2.60%	-5.24%	26	-4.64%	-2.30%	-6.33%
2010	14	1.99%	-1.05%	-0.47%	16	1.95%	-0.81%	-0.34%	3	0.74%	4.34%	5.77%	16	-0.57%	0.02%	-0.11%
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	2.43%	-0.76%	1.19%	5	-1.71%	-2.58%	-4.19%	17	-0.85%	-1.42%	-1.74%
2013	11	2.45%	1.54%	3.01%	19	2.08%	1.05%	2.23%	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	0.89%	-1.26%	-0.05%	7	4.18%	1.67%	6.31%	28	1.95%	-0.55%	1.85%
2017	19	0.47%	0.18%	-0.26%	26	0.57%	-0.40%	-0.21%	11	1.35%	-0.80%	-0.40%	27	1.12%	-1.36%	-0.33%
2018	21	0.09%	0.67%	-1.04%	24	0.06%	0.51%	-1.16%	8	-0.28%	0.44%	-2.09%	23	0.19%	0.46%	-0.28%
2019	12	0.28%	0.95%	0.90%	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%