The Flattening Demand Curves

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Abstract

This study examines the price impact of nonfundamental demand shifts on index listed stocks whose weight in the index portfolio was forced to change due to the disparities between the weights of newly added and removed stocks during index reconstitution events. Findings show that the demand curve of stocks has flattened in the recent two decades due to lower risk of arbitrage activity.

Keywords: Index Effect, Index Reconstitution, Index Funds, Price Pressure, Elasticity of Demand.

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[‡]The main pillar of data for this research paper is the weights of S&P 500 constituents which are obtained directly from SPDJI. Notice is given that the views expressed herein are those of the author and do not necessarily reflect the views of any institution.

1 Introduction

An equity index is a composite measure that tracks the performance of a specific group of stocks, serving as a benchmark for assessing market trends and comparing investment returns. Index reconstitutions induce large demand shifts from passive index funds that mimic the index portfolio. The index effect refers to the abnormal return experienced by stocks added to or removed from a major equity index, initially documented in the seminal works of Shleifer (1986) and Harris and Gurel (1986). This critical observation challenges the efficient market hypothesis and creates opportunities for investors to capitalize on market inefficiencies.

The efficient market hypothesis proposes that the price of a stock equals its expected future cash flows discounted by systematic risk. This perspective in neoclassical finance theory results in virtually flat demand curves for stocks (see Petajisto (2009) for detailed derivations). Thus, if one believes that changes in stock indices do not contain any information, it becomes challenging to rationalize the observed index effect within the framework of the efficient market hypothesis. Consequently, initial investigations into this subject either inferred that index changes are not devoid of information (Denis et al., 2003; Chen et al., 2004; Cai, 2007) or that the market's efficiency is compromised, leading to downward-sloping demand curves for stocks (Shleifer, 1986; Harris and Gurel, 1986).

Assessing the potential factors that contribute to the index effect, particularly focusing on demand and information, has become progressively intricate due to a recent observation: Despite the significant growth of passive investing, there has been a secular decline in the magnitude of the index effect in recent decades. This observation presents a puzzling scenario since, even when assuming a downward-sloping demand curve with a constant elasticity, one would expect larger price reactions if demand shocks were increasing in magnitude. This study aims at revisiting the index effect literature in search for origin of the observed abnormal returns, their determinants, and the reason for their decreasing trend. By addressing these research questions, this study provides insights into the evolving nature of the efficiency in financial markets. My findings show that demand is the main driver of the index effect, and the decreasing trend of index effect is due to the general flattening of stocks' demand curves, which extends beyond index reconstitutions and their associated informativeness.

Theories that attempt to explain the index effect are broadly classified into demand-based and information-based groups. The former group associates abnormal returns with the inelastic demand of passive index followers who buy the added firms and sell the deleted firms regardless of their prices. On the other hand, the latter group subscribes to the notion that index events convey new information to the market, which in turn moves the prices. Especially when an index is not rule-based, as is the case with the S&P 500[1], investors naturally assume that there is a rationale behind every index decision and that index announcements convey information. The S&P 500 index is an ideal candidate for investigating the information content of index events due to its non-mechanistic nature and reliance on subjective decision-making. The index committee, composed of financial experts with first-hand information, makes all decisions, thereby rendering their determinations indicative of relevant underlying information in the eyes of the market. In contrast to fully transparent and rule-based indices, information-based explanations hold significant relevance for subjective indices such as the S&P 500.

To assess the relative explanatory power of demand-based and information-based theories in explaining the index effect, I propose a novel identification that shifts the focus from the added and deleted firms to other index members that were not actively involved in the reconstitution events. The size of added and deleted firms often differs significantly, resulting in a disparity in their respective portfolio weights. As a result of this asymmetry between the weight of added and deleted firms, the weight of other index firms in the portfolio must change to maintain a total weight of one. These firms are referred to as index incumbents, as they were index constituents both before and after the reconstitution event. The sole effect of reconstitution on these firms is the possible adjustment of their weight in the index composition and the following mechanical rebalancing of index trackers. Therefore, index events are free of any information about these firms, and any abnormal return on these stocks around the reconstitution can be associated with demand. Studying the effect of such *information-free* demand shifts on incumbents' prices enables me to predict what would be the abnormal returns for the added and deleted stocks if there was no informational component in the index effect. In other words, this strategy enables me to pin down the counterfactual price reaction to an information-free demand shift and to juxtapose this counterfactual with the actual abnormal returns observed on additions and deletions.

The first contribution of this paper is to explore the driver and determinants of index effect. I empirically link the size of the price pressure experienced by a stock to the magnitude of the shock in its index weight. My results show that the observed abnormal returns on additions and deletions are in the same order of magnitude that an information-free demand shift predicts, implying that demand is the primary driver of the index effect.

[1]Different stock market indices use varying methods and criteria to select and weigh their constituent stocks. Some indices, like the FTSE and NASDAQ, are fully transparent and rule-based, making it relatively manageable to predict which stocks will be included or excluded (Danbolt et al., 2018). However, other indices like the Russel and CRSP are also rule-based and transparent, but their changes are not entirely predictable (Chang et al., 2014; Heath et al., 2020). Finally, there are indices like the S&P family, whose inclusion or exclusion of stocks is decided by a committee and does not follow a fixed schedule.

Although earlier studies such as Denis et al. (2003) present compelling evidence for the informativeness of index decisions in an older sample of additions, my analysis shows that this phenomenon no longer seems to hold. The key finding is that demand independently accounts for the entire average effect size. In other words, to justify the average abnormal return on added and deleted stocks, generally known as the *index effect*, demand-based explanations are sufficient. Information-based explanations[2] can be compared in analogy to regressors with statistically significant coefficients which do not significantly contribute to the overall explanatory power of the model (i.e., the R-squared value).

The second contribution of the paper, which pertains to methodology, is a novel identification strategy to isolate the price effects of a pure demand shift, as distinct from price changes due to fundamentals or news. The challenge in accurately estimating micro elasticities in a reduced-form fashion is that the effects of demand and information on prices are often convoluted, especially when incorporating substantial demand shifts in estimations. This problem is the principal criticism leveled at studies that estimate the elasticities using the price effects of index additions and deletions. By shifting the focus from an information-intensive demand shift on additions and deletions to an information-free demand shift on index incumbents, my findings show that, holding all other factors constant, a demand shock equivalent to one percent of the total shares outstanding generates a price movements of roughly 40 basis points, implying a micro elasticity of index funds' demand in the order of -2.5.

I derive a measure, which I term as *Mechanical Rebalancing Flow* (MRF), that captures the aggregate inelastic demand shift of all passive index trackers. Specifically, I define MRF as the amount of money pumped into or withdrawn from stocks by passive funds purely due to the adjustment in index composition relative to the stock's market capitalization.

The findings of this study indicate the following. First, MRF, as an instrument for demand shifts, is positively associated with the price reaction, volume of trades, and volatility of prices around the index reconstitutions. However, the relationship between

[2]The literature review in the following section will highlight that information-based explanations for the index effect can manifest in various forms in addition to the literal meaning of information, including investor attention, market awareness, liquidity enhancement, and a reduction in information asymmetry. It is crucial to emphasize that not all factors outside the demand realm can be classified as information. Hence, the term "informational components" is prudently employed instead of "information" to emphasize the diversity of these factors. The paper rules out the aggregate net effect of such informational components but doesn't comment on every one of such explanations. This decision is partly because some informational components, such as market awareness, move slowly and do not have an adequate measure in daily frequency. Consequently, any analysis involving them must inevitably use an extended timeframe which makes it unreasonable to attribute abnormal returns that occurred in a few days to such slow-moving variables, even if the abnormal returns are assumedly realized due to the market participants expecting an improvement in these variables.

price movements and MRF weakens over time, with the majority of effects being driven by the earlier part of the sample. This result suggests that while the demand curves for stocks generally slope downward, they have significantly flattened in recent years. This critical finding of the paper is the key to address the puzzling phenomen of shrinking index effect magnitude despite the surge in passive investing. Second, I show that the risk of arbitrage activity, measured as the residual of regressing one stock's excess return on that of a group of possible substitudes, acts as a channel moderating the effect of demand shifts on prices, such that prices of stocks with close substitutes that are hence easier to engage in arbitrage activity are less sensitive to demand shifts. This empirical finding also reveals that the reduction in price impact multiplier, which is the negative inverse of the price elasticity of demand for stocks, is partially due to a documented decrease in overall arbitrage risk of stocks. Third, the risk of arbitrage activity and hence micro price impact multiplier are both strongly linked to the overall capability of the market to provide liquidity. While these variables generally exhibits a decreasing time trend, they spike during financial crises and the COVID-19 pandemic when there was a marketwide liquidity shortage.

This study also contributs to the literature on predictable price pressure[3]. To the best of the author's knowledge, this research is the first to show that abnormal returns are not only observed among additions and deletions during index reconstitutions but also among other index incumbents. These abnormal returns that depend on the size and direction of incumbents' weight adjustment, are roughly - 4 and +4 bps, respectively in the first and last quartile of weight adjutments. The sign of these abnormal returns depends on whether the added stock is of a larger size or the deleted one. In cases where the addition is larger, index incumbents experience negative abnormal returns as index funds need to sell their holdings in order to allocate a larger weight to the newly added stock. Conversely, when the deletion is larger than the addition, index incumbents exhibit positive abnormal returns. These epirical findings offer valuable insights into the broader implications of index composition changes, as they happen around the effective day while the index decisions were announced in advance rendering these weight shifts broadly predictable.

The closest empirical works to this research are Pavlova and Sikorskaya (2022), and Greenwood and Sammon (2022). Pavlova and Sikorskaya (2022) investigate the effects of

[3]Among others, Hartzmark and Solomon (2022) show that uninformed cash flows forecast aggregate market stock returns, Parker et al. (2020) show mechanical re-balancing by target date funds influences the crosssection of stock returns and overall market dynamics, and Lou et al. (2013) show that the treasury security prices in the secondary market decrease significantly in the few days prior to treasury auctions and recover shortly thereafter, while the time and amount of such auctions are announced in advance.

stock membership in multiple indices to funds' demand, prices, and expected returns using an extensive group of US equity indices. In a contemporary contribution, Greenwood and Sammon (2022) explore five reasons behind the decreasing magnitude of the index effect and conclude that the decline is akin to other anomalies that tend to diminish once they become well-known. My research differs from theirs for its focus on overall sensitivity of stock prices to demand shifts, beyond index additions and deletions. Specifically, I establish that the average magnitude of the index effect can be primarily explained by a demand model featuring time-varying price impact sensitivity and the decline in the index effect is attributable to the flattening of stocks' demand curves, which extends beyond index composition changes and their potential informativeness.

The paper proceeds as follows: Section 1.1 presents a literature review on the index effect and explains the proponents of demand-based and information-based explanations in more detail. Section 2 sheds light on the demand shift measure construction and presents the theoretical framework, identification strategy, and hypotheses. Section 3 describes the data. Section 4 presents the empirical results, and the last section concludes.

1.1 Literature Review

The literature on the index effect offers various theories to explain the size, permanency, and symmetry of the effect for additions and deletions. See Afego (2017) for an extensive review of this literature. These explanations fall into two main categories: demand-based and information-based theories.

Demand-based theories attribute the index effect to the large and inelastic demand from passive index trackers. Notable within this category are the price pressure and imperfect substitute hypotheses. The price pressure hypothesis asserts that short-term demand shifts lead to temporary price changes (Harris and Gurel, 1986; Mase, 2007; Danbolt et al., 2018). The imperfect substitute hypothesis suggests long-lasting price effects because index funds' excess demand could be met without a price change only if stocks had perfect substitutes (Shleifer, 1986; Beneish and Whaley, 1996; Lynch and Mendenhall, 1997; Kaul et al., 2000; Wurgler and Zhuravskaya, 2002; Fernandes and Mergulho, 2016).

Information-based theories propose that index reconstitutions somehow change the market expectation of the involved stock and thereby communicate new information about firms' prospects. These explanations encompass various hypotheses based on different driving forces.

The literal meaning of information serves as the first proponent of information-based explanations. From this viewpoint, inclusion in a major index indicates the firm's recognition as an industry leader or an enhancement in management quality. This hypothesis finds support in the strong inclination of the index committee to minimize index turnover. A low index turnover is crucial in enhancing index popularity as it facilitates index replication for followers while reducing tracking errors and transaction costs. Consequently, the index committee strives to include only those stocks in the index that are reasonably expected to maintain long-term and robust membership. Along these lines, firms also take pride in their inclusion in the S&P 500 index and highlight its subjective decision-making in their market communications. For example, Red Hat communicated its inclusion in S&P as follows[4]: "*Red Hat was* ***chosen*** *by Standard and Poors for inclusion in the Standard and Poors 500 stock index... It includes 500* ***leading*** *companies of the U.S. economy, ... The inclusion of Red Hat into the S&P 500 is an important* ***recognition and a source of pride*** *for Red Hat associates ....*"

Denis et al. (2003) examine the informational content of S&P 500 reconstitutions by investigating analysts' earnings forecasts around the index event and comparing post-inclusion realized earnings to pre-inclusion forecasts. Their findings reveal that analysts exhaustively revise their forecasts upward following a firm's inclusion in the S&P 500, leading to a significant subsequent reduction in their forecast errors. Their analysis strongly suggests that S&P 500 index inclusions were not devoid of information during their sample period. In another study, Cai (2007) examines information content of S&P 500 index changes by examining the price and volume reaction of the industry and size matched firms. He also finds that index addition conveys favorable information about the added firm and its industry. It is worth noting that both mentioned studies utilize a sample predating the 2000s. Contrary to theirs, my analysis shows that S&P 500 additions and deletions no longer seem to convey information.

The second information-based explanation suggests that index effects stem from liquidity changes. The liquidity hypothesis proposes that analysts' increased attention to added firms improves information production, reducing information asymmetry and boosting liquidity. Improved liquidity then results in lower required returns and higher prices for added stocks (Amihud and Mendelson, 1986; Chen et al., 2004). While past studies partially support this idea, my analysis yields mixed outcomes. Investigating liquidity shifts in added and removed stocks, I find inconsistent bid-ask spread changes and temporary trade volume surges around the event, reverting soon after.

Closely tied to the liquidity hypothesis is the investor attention hypothesis, suggesting that heightened visibility spurs improved management performance (Denis et al., 2003). However, in a recent study, Bennett et al. (2021) demonstrate that the greater public

[4]announcement can be found at https://www.redhat.com/en/blog/red-hat-included-in-sampp-500-index

scrutiny could also hurt a firm's performance. They show that elevated attention after index inclusion often associates with declining post-inclusion performance. My study expands their analysis to index deletions and finds that not only does performance decline for added firms, but it also improves for discretionary deletions - firms removed from the index not due to delisting but by index committee choice.

The last form of information-based theories is the awareness hypothesis, which posits that the inclusion of a firm in an index enhances investors' awareness of its existence. Drawing upon Merton et al. (1987) model of market segmentation, this hypothesis suggests that if certain investors are only aware of a subset of all stocks and hold only those stocks, they may lack adequate diversification and therefore demand a premium, known as the shadow cost, for the nonsystematic risk they bear. When a stock enters the S&P 500, broader ownership due to increased awareness can lower the required return by reducing the shadow cost.

The investor awareness hypothesis is particularly potent in justifying asymmetric effects observed on additions and deletions in their size and permanency. As Chen et al. (2004) puts it, "while more investors become aware of stocks added to the index, the number of investors aware of deleted stocks may not actually fall because it may be difficult for investors to become 'unaware' of those stocks." Similar to Chen et al. (2004), my findings reveal that the average cumulative abnormal return for additions stabilizes at a positive level after the event. However, my findings also show that this stabilization pattern extends to discretionary deletions when they are distinguished from forced deletions.

2 Theory and Identification

The total weights of constituents in the index portfolio naturally always add up to one. During an index reconstitution event, the weights of added and dropped stocks typically differ from each other[5]. As a result, the weights of the other index incumbents need to adjust in order to maintain a total weight of one. The first part of this section employs the weighing scheme employed by S&P 500 to quantify the demand shifts that arise from the mechanical portfolio rebalancing carried out by index funds. The second part outlines the identification strategy and formalizes the hypotheses to be tested.

[5] In section 4.2, I will demonstrate that the average index addition is more than twice the size of the average discretionary deletion.

2.1 Theoretical Framework

The weight of an index constituent j in S&P 500 at the closing of the trading day t is calculated by the following equation

$$w_t^j = \frac{P_t^j S_t^j IWF_t^j}{\sum_{i=1}^N P_t^i S_t^i IWF_t^i}, \tag{1}$$

where, for the day t and stock j, P_t^j is the stock price, S_t^j is the total shares outstanding, and IWF_t^j is the Investable Weight Factor[6], all measured at the close of markets. N is the number of constituents in the index, typically 500 for S&P 500. IWF is the measure of float adjustment, which is an attempt to enhance the investability of the index by excluding shares of strategic shareholders in calculating firm market capitalizations[7]

Index level[8] is calculated as

$$Ind_t = \frac{\sum_{i=1}^N P_t^i S_t^i IWF_t^i}{Divisor_t}, \tag{2}$$

in which the denominator is the index divisor at the close of day t. The index divisor serves two purposes: first, dividing the free-float market value of the index by this factor does a scaling that helps market participants to work with a more easily handled number (e.g., 2000) rather than dealing with ten or more digits when reported in dollars. Second, and more crucial to this research, it is used as a level corrector to maintain the continuity of the index level following the implementation of corporate decisions, index reconstitutions, or other non-market-driven actions. Hence, the index divisor serves as the channel through which the difference in weight of added and deleted stocks affects the weights of other constituents in the index, ensuring that the sum of weights remains equal to one.

Equation 2 yields $\sum_{i=1}^N P_t^i S_t^i IWF_t^i = Ind_t * Divisor_t$, which enables us to rewrite Equation 1 as

$$w_t^j = \frac{P_t^j S_t^j IWF_t^j}{Ind_t * Divisor_t}. \tag{3}$$

[6] IWF of a stock is simply the ratio of floating shares to total outstanding shares. For instance, an IWF of 0.8 for stock j indicates that 80 % of total shares outstanding of that stock are freely tradable and available to the marketplace, and the rest 20% are held by strategic investors that are not expected to liquidate their position any soon. IWF's are crucial data used in determining constituents' weights. They are the key missing point preventing investors without S&P data subscription from replicating the index even if they have the list of included stocks.

[7] The list of shareholders that S&P deems strategic goes long. The most important are control groups, seatholders, publicly traded companies, and government agencies. For an extensive list, please consult S&P Float Adjustment Methodology document at the S&P Dow Jones Indices website at this address: https://www.spglobal.com/spdji/en/documents/index-policies/methodology-sp-float-adjustment.pdf

[8] Index level in this paper always refers to the S&P 500 price index level, which is commonly referred to in the news and statistics. S&P 500 total and net return index are then calculated based on the price index.

Therefore, the ratio of the weights of an index constituent j in the closing of two consecutive trading days would be

$$\frac{w^j_{t+1}}{w^j_t} = \frac{R^j_{t+1}}{R^{Ind}_{t+1}} * \frac{S^j_{t+1}}{S^j_t} * \frac{IWF^j_{t+1}}{IWF^j_t} * \frac{Divisor_t}{Divisor_{t+1}}, \tag{4}$$

where R^j_t and R^{Ind}_t are respectivey the gross returns of the stock j and the S&P 500 price index in day t. The decomposition in Equation (4) shows that any change in the weight of a stock from one day to the next comes from one or some of these four ratios.

The first ratio in Equation (4) represents the stock price growth relative to the index. It is important to note that for an ideal index fund that closely replicates the index portfolio, changes in this component of weight do not necessitate portfolio rebalancing[9]. In other words, if there are no shocks affecting the stocks and only price movements occur, the value-weighted portfolio will remain correctly value-weighted.

In contrast to the first ratio, index funds must rebalance their portfolios if any of the remaining three ratios in Equation 4 is not equal to one. Although daily changes in index divisor are widespread, the amount of weight change that firms incur only because of the modification in the index divisor is free of information about each specific firm. Even the changes on the IWF and outstanding shares do not contain new information about stocks since index maintenance requires a holding period before implementing the changes on their calculations[10]. Except in rare cases, these numbers are often revised only on annual rebalancings.

Aiming to find a measure of fund flows implied by the index funds' mechanical rebalancings, I define the shocks to the weights of index incumbents that require rebalancing for index followers as Δw^j_{t+1} that is calculated as follows:

$$\Delta w^j_{t+1} = w^j_t * \frac{S^j_{t+1}}{S^j_t} * \frac{IWF^j_{t+1}}{IWF^j_t} * \frac{Divisor_t}{Divisor_{t+1}} - w^j_t. \tag{5}$$

Intuitively, Δw^j_{t+1}, is the weight of stock j in the index portfolio one moment before

[9] For instance, assume the index return is zero in a day t ($R^{Ind}_t = 1$) and some stock j has a return of 1% on that day ($R^j_t = 1.01$). Also, assume the other three ratios are equal to one, which means there is no stock repurchase or equity issue for this stock, no change in the number of floating stocks, and no change in the index divisor on that day. Suppose the index fund already had the right number of shares at the previous day's closing (i.e., proportional to the weight of this stock in the index at the close of the market). In that case, it will automatically have the correct number of shares at the closing of day t, which is, in fact, the same number of shares! However, this number of shares results in 1% more weight in the index today than the previous day, precisely as it should. I assumed this fund had no net inflows or outflows on this day.

[10] For this reason, I also use SPDJI data as reference for the number of shares outstanding in the calculation of weight surprises.

the markets opened on the morning of the day $t+1$ minus the weight this stock had at the close of trading at day t. To fix ideas, assume the index divisor increases overnight after the close of markets in day t ($Divisor_t < Divisor_{t+1}$,) which means that the total floating market value of index constituents has increased after the close of trading (for instance, because the next day is the effective day of an index reconstitution in which a large firm replaces a small firm in S&P 500.) Then the weight of an average firm (with no change in S and IWF) in the index has to decrease, and Δw^j_{t+1} will be negative since $Divisor_t/Divisor_{t+1} < 1$.

I define the measure of fund flows implied by mechanical (information-free) rebalancing as follows:

$$MRF^j_{t+1} = \frac{A_{t+1}\Delta w^j_{t+1}}{S^j_t P^j_t}. \tag{6}$$

MRF stands for Mechanical Rebalancing Flow, and $A_{t+1} = \sum A^F_{t+1}$ is the total amount of dollars invested in passive funds are benchmarked against S&P 500 in the opening of the day $t+1$. MRF measures the surprises in the inelastic demand of an ideal index fund, similar to the measure constructed and used in Pandolfi and Williams (2019) for a weight-capped bond market index. Here, instead of the cap on the constituents' weights, MRF is built upon the weight spillovers on index incumbents through the index divisor changes.

To put it simply, MRF^j_t captures the amount of money that will flow into or out of an stock j at day t, relative to its market value in the previous trading day, as a result of mechanical rebalancing of index followers regardless of the stock's individual characteristics or fundamentals. Based on this intuitive definition, I can extend the definition of MRF to additions and deletions, in which case I will use w of the added stock or $-w$ of the deleted stock instead of Δw in the MRF formula. Note that, for example, for an addition in day t, Δw reduces to w simply because that stock had zero weight in the index portfolio on the previous day.

2.2 Identification and Hypotheses

The identification assumption in pinning down the causal effect of demand in this paper is that a stock whose weight has increased (decreased) by an amount of Δw^j_t, and a company that has been added to (dropped from) the index in day t with a weight of w^i_t, both experience an equal inelastic demand from the index funds up to the level of their market caps. In an overly simplified example, if these two firms had similar market capitalizations, and $w^i_t = \Delta w^j_t$, the experienced demand shift on these two firms would be identical. Thus, the difference between the experienced abnormal returns on such two stocks must be attributed to the non-demand-driven components of the index effect.

The central hypothesis revolves around testing the effect of MRF, as the measure of information-free demand shifts, on prices and other variables of interest. Formally, I will run the following regression in time-invariant settings:

$$y_{jt} = \beta MRF_t^j + \phi X_{jt} + \theta_t + \theta_j + \varepsilon_{jt}, \tag{7}$$

where y_{jt} is the dependent variable, θ_t and θ_j are fix effect dummies, and X_{jt} represents other control variables. Notably, β will quantify the causal effect of nonfundamental demand shifts on the outcome variables. For the models with time varying sensitivity, I will estimate the conditional model by replacing β with β_t in the equation as follows:

$$y_{jt} = \beta_t MRF_t^j + \phi X_{jt} + \theta_t + \theta_j + \varepsilon_{jt}, \tag{8}$$

in which $\beta_t = \sum_p \beta_p \mathbb{1}(period = p)$. This approach allows me to estimate different coefficients for different periods when the sample time in devided into multiple periods.

3 Data

The primary sample is the list of S&P 500 constituents and their daily weights in the index composition. I obtain this data directly from S&P Dow Jones Indices (SPDJI.) Daily stock data and quarterly fundamentals are from CRSP and Compustat. Risk-free return and market return are from Kenneth R. French's website[11]. Index funds list, their prospectus benchmark, and their assets under management are from Morningstar. Index composition changes for S&P 500, S&P 400, and S&P 600 come from Siblis research. The sample period is January 2000 to June 2021, determined by the daily index constituents' data from SPDJI. All daily measures from CRSP are winsorized at 0.1% from each tail.

I received the list of index composition changes separately from Siblis research and SPDJI and combined them. In cases of mismatch in effective dates between the two lists, I obtain the correct effective date of index changes directly from the list of daily constituents data from SPDJI. In case of a mismatch in announcement dates and tickers, I manually correct the list based on CRSP data and financial news online sources. This combined list includes 1143 index composition changes. From the combined list, I dropped 37 events (74 additions and deletions) in which a stock was added to the index and then quickly removed. These are either spin-offs of an S&P 500 firm that S&P decided not to keep in the index or placeholders that are stock in S&P 500 to keep the number of constituent

[11] www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

firms at 500 when there was a gap between the addition's and deletion's effective dates. I further dropped 9 cases (18 additions and deletions) where the addition was created due to a name change on the deletion (for example, as the result of a merger), and index funds did not have to buy or sell any shares.

The final sample contains 528 additions and 523 deletions, all successfully identified in CRSP. The number of additions and deletions differ because, in five cases, S&P added a second share class of another S&P 500 firm, which does not count against the number of constituent firms. Thus, these additions were not coupled with a deletion. As a result of such additions, S&P 500 currently has 505 securities. Lastly, these 1053 index events list 424 announcement dates and 446 effective dates that will be used to make the sample index incumbents. Out of 528 additions, 264 and 4 additions were migrations from S&P 400 mid-cap and S&P 600 small-cap indices and from 523 index deletions, 131 and 18 deletions were migrations, respectively to S&P 400 mid-cap and S&P 600 small-cap indices.

I further divide the index events into forced and discretionary based on the trading status of the deleted firm after the event. Forced index events are those in which the index deletion was delisted entirely from the exchange within a week[12] from the deletion effective date. Regardless of why these stocks were delisted, the index committee had to drop them from the index simply because they wouldn't be trading anymore. The discretionary events are those that were not forced. In other words, the index committee chose to drop those stocks, even though they continued trading after the event.

Abnormal returns are calculated using Carhart (1997) four-factor model. The estimation window is 252 days (one year) using daily stock returns, requiring at least 100 observations within the window. The estimation window ends two weeks before the effective day for additions[13] and deletions to reduce the likelihood that the model estimation would be affected by the index event. For index incumbents, I used the most recent estimates.

The sample of index incumbents includes all S&P 500 securities, in the reconstitution effective dates, except the stocks that were just added. I further drop the forthcoming deletions by filtering on having the incumbents still present in the index within one week. Table 1 presents the summary description of the data.

Table 1 also reports the summary description for index additions and deletions, sep-

[12] I verify that the choice of the period does not have any meaningful effect on the results. From all the deletions that were delisted within three months of the effective date, more than 80% were already delisted one day after the effective day.

[13] For the parts of analysis related to abnormal returns, a further number of 63 additions were excluded either because they were new securities and didn't have a price observation before the event (for example they were the result of a merger between two S&P firms), or failed to have the minimum number of required observation for coefficient estimations.

Table 1: Summary statistics

Variable	Mean	p25	p50	p75	SD	N
Index Incumbents						
$MCap_{eff}$ (B$)	29.56	12.66	27.05	6.35	60.48	221716
$Weight_{eff}$ (%)	0.20	0.09	0.18	0.05	0.36	221716
$MRF(*10^{-4})$	0.01	-0.09	0.04	-0.23	8.32	221716
β^{CAPM}	1.00	0.96	1.24	0.71	0.47	221715
Iwf	0.97	1.00	1.00	1.00	0.09	221716
$Growth$	0.41	0.39	1.00	0.00	0.43	221716
$TurnOver$	0.01	0.01	0.01	0.00	0.01	221716
$BidAskspread$ (%)	0.22	0.04	0.11	0.02	0.64	214289
$Range_t$	0.03	0.02	0.04	0.01	0.02	221716
$Ann\ to\ Eff$	4.81	5.00	6.00	3.00	2.07	221716
Index Additions						
$MCap_{eff}$ (B$)	13.53	9.68	13.37	6.16	31.93	471
$Weight_{eff}$ (%)	0.10	0.06	0.09	0.05	0.14	528
$MRF(*10^{-4})$	417.54	371.35	531.81	272.97	211.60	471
β	1.09	1.02	1.36	0.73	0.56	464
Iwf	0.94	1.00	1.00	1.00	0.12	528
$Growth$	0.61	0.66	1.00	0.25	0.40	528
$Turnover$	0.03	0.02	0.03	0.01	0.02	528
$Bid\ Ask\ spread$ (%)	0.20	0.04	0.13	0.02	0.58	515
$Range_t$	0.03	0.03	0.04	0.02	0.03	471
$Ann\ to\ Eff$	5.36	5.00	6.00	4.00	3.03	528
Discretionary Index Deletions						
$MCap_{eff}$ (B$)	5.79	2.87	4.74	1.21	14.94	243
$Weight_{eff-1}$ (%)	0.04	0.02	0.03	0.01	0.09	243
$MRF(*10^{-4})$	-395.78	-400.42	-263.32	-505.73	160.97	243
β	1.30	1.28	1.65	0.85	0.65	243
Iwf	0.96	1.00	1.00	1.00	0.11	243
$Growth$	0.19	0.00	0.37	0.00	0.34	243
$Turnover$	0.04	0.03	0.05	0.02	0.03	240
$Bid\ Ask\ spread$ (%)	0.78	0.10	0.35	0.05	2.18	233
$Range_t$	0.07	0.05	0.08	0.03	0.06	240
$Ann\ to\ Eff$	5.35	5.00	6.00	4.00	1.98	243
Forced Index Deletions						
$MCap_{eff}$ (B$)	17.38	10.73	22.11	5.84	18.23	278
$Weight_{eff-1}$ (%)	0.12	0.08	0.15	0.04	0.13	278
$MRF(*10^{-4})$	-392.18	-355.63	-283.41	-498.08	149.70	278
β	0.81	0.71	1.06	0.46	0.54	280
Iwf	0.98	1.00	1.00	1.00	0.08	278
$Growth$	0.37	0.00	0.71	0.00	0.42	278
$Ann\ to\ Eff$	5.24	5.00	6.00	3.00	3.80	278

This table presents the summary description of sample stocks. Deleted firms are divided into forced and discretionary. Reported β is from the market model using an estimation window of 252 days (one year), requiring at least 100 observations within the window. IWF is the investable weight factor. Bid ask spread is reported as the percentage of mid-price. If necessary, the unit of measure is reported before the variable's name. The sample period is (2000-01, 2021-06).

arating deletions into forced and discretionary. Regarding market capitalization, index additions are larger than discretionary index deletions but smaller than forced index deletions. Index additions exhibit a smaller bid-ask spread, while their turnover is comparable. Most liquidity measures are missing for forced deletions since they don't have an observation in CRSP on the effective day, so they were not reported. The distance between announcement day and effective day for both additions and deletions is highly concentrated around five trading days. For index incumbents, on each reconstitution day, I take the minimum of this distance between all additions and deletions on that day, capped at two weeks.

Index funds' data are obtained from Morningstar. From the universe of passive funds, I collected the data for the funds tagged as index funds (both open-end funds and ETFs) and had S&P 500 as their primary prospectus benchmark. Figure 1 shows the total assets under management of index funds and their their aggregate percentage holding of an exemplary index firm with full float ($IWF = 1$.) In early 2000, index funds' total AUM was nearly USD 240 billion, and they collectively held about 2% of shares of a full-float index firm[14]. In 21 years, the total AUM of index funds rose by more than ten times to USD 2.5 trillion, and they were holding about 7% of total shares outstanding of full float index firms. The difference in the growth of the two numbers shows that most of the rise in the AUM of index funds comes from money inflow to these funds as opposed to organic capital gains in the stock market.

4 Empirical Results

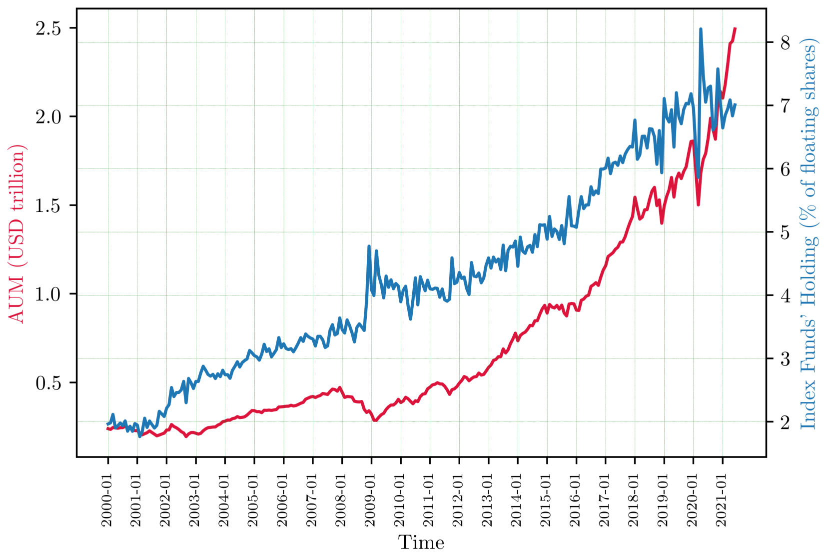
The first part of this section studies the effect of index reconstitutions on index incumbents. The other two parts focus on the added and deleted stocks. In the second part, I will measure the abnormal returns of index additions and deletions and determine to what extent a pure demand shift can justify them. The last part studies the long-term returns of index additions and deletions and their fundamentals.

4.1 Index Incumbents

This section shows that the defined measure of mechanical demand, MRF, explains the price reaction for index incumbents, quantifies the price impact and price elasticity of demand, discusses the time trend of these variables, and pins down a model to form

[14]For firms that are not full-float, the percentage of shares held by index funds is reduced according to their IWF. For example, the percentage of total shares outstanding collectively held by passive index trackers in a firm with $IWF = 0.5$ is half of that of a firm with full-float, regardless of their market cap.

Figure 1: Total assets under management and percentage holding of index funds



This figure shows the total assets under management of passive index funds benchmarked to S&P 500 and their aggregate percentage holding of stocks in (2000-01, 2021-06). The red line shows the assets under management in USD trillions, and the blue line shows how many percentages of an index firm with $IWF = 1$ is held collectively by index funds at each month.

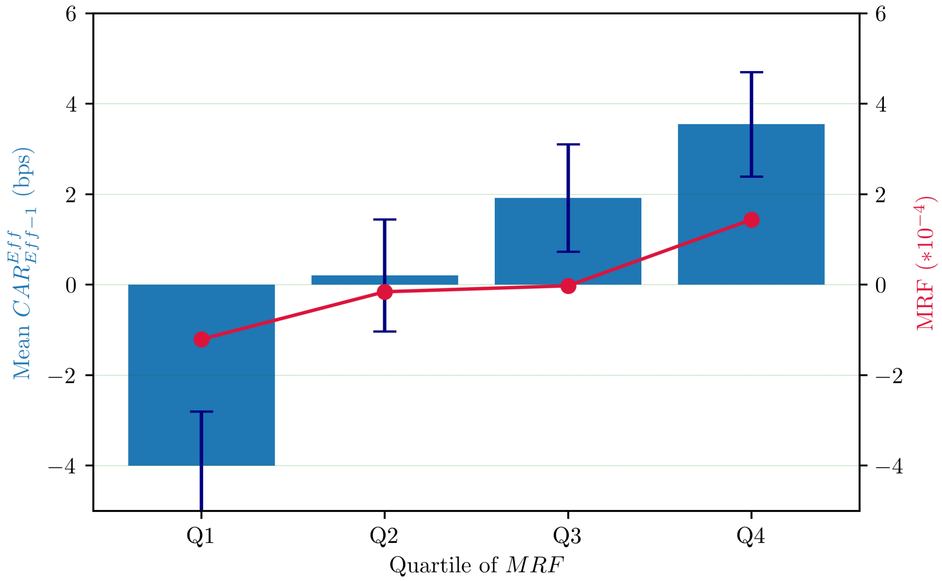
a counterfactual information-free demand response on additions and deletions in the following sections.

4.1.1 Price Impact

Figure 2 examines the relationship between the magnitude and direction of incumbents' weight adjustment and their corresponding price reactions. To accomplish this, I partitioned the incumbent sample into quartiles based on their MRF and calculated the mean of the two-day cumulative abnormal return during the reconstitution's effective date and the preceding day for each quartile. The graph clearly illustrates a steady rise in returns as MRF increases, indicating a positive association between the explanatory variable and the return in a straightforward setting. The choice of the two-day period, including the effective date and the preceding day, is motivated by the behavior of passive index funds. Aiming to minimize tracking error, index funds rebalance their portfolios as close as possible to the actual reference change that would be either on the effective day or the day preceding it.

Table 2 presents the association of MRF with returns using the regressions in Equation (7). Each regression studies the impact of demand shift on a specific measure of price changes. Consistent with demand hypotheses, all else equal, price reactions are larger for stocks experiencing larger shifts in their weights. I focus first on the full sample

Figure 2: Price reaction to nonfundamental demand shift



This figure shows the two-day cumulative abnormal return of index incumbents, in the effective date of index reconstitutions and the day before it, in reaction to the change of their weight in the index portfolio. Vertical axis represents the quartile of the demand shift, measured by MRF. The mean of MRF in each quartile is shown by the red line. Navy blue bars represent 95% confidence intervals. Sample period is (2000-01, 2021-06).

estimates and then divide the sample into two equal parts (each eleven years) to observe the structural breaks. All regressions include controls in addition to stock and day fix effects. Control variables are log MV (the logarithm of proprietary total market value), IWF (proprietary float factor), β^{CAPM} (loading on the market in the one-factor market model), and the liquidity (average daily turnover of the stock in the previous month).

The full sample estimates in Table 2 show that a 1% MRF or equivalently, buying 1% of shares outstanding, leads to about 24bps higher return in that trading day, from which 19 bps are realized just on the opening batch auction[15]. I define the daily opening return of stocks as $(P_t^{open}/P_{t-1}^{close} - 1)$ corrected for dividends and stock splits. Interestingly, the entire 23 bps price reaction in response to MRF ends up in the abnormal return of that stock on that day. This fact shows that heterogeneity in the price movement of stocks is due to the heterogeneous surprises in their weights. Thus, the market movement, size,

[15]The opening batch auction is a process that occurs before continuous trading begins for the day and is used to determine the opening price for securities. During this time, buy and sell orders are matched and executed at a single price point. The closing auction is similar to the opening auction in that it is a process used to determine the closing price for securities, and it involves matching buy and sell orders at a single price point. Market participants can enter orders to buy or sell securities at the closing price during the closing auction. The auction is typically held a few minutes before the end of the trading day, and the closing price is determined by the price at which the maximum volume of shares can be traded.

Table 2: MRF and return

Dependent Variable	(1) Ret_t	(2) Ret_{t-1}	(3) Ret_t^{open}	(4) CAR_{Ann}^{Eff}	(5) CAR_{Ann}^{Eff-1}	(6) CAR_{Eff-1}^{Eff}	(7) AR_{Eff}	(8) AR_{Eff-1}	(9) AR_{Eff-2}
Full Sample (2000-2021)									
MRF	0.237**	0.127	0.192***	0.420**	0.164	0.380**	0.256**	0.124	0.060
	(2.16)	(1.14)	(2.80)	(2.37)	(1.51)	(2.25)	(2.33)	(1.29)	(0.71)
Adj. R-sq	0.372	0.346	0.352	0.017	0.017	0.015	0.014	0.012	0.011
N	221715	221715	221281	221692	221692	221715	221715	221715	221708
Early Sample (2000-2010)									
MRF	0.491***	0.429	0.348***	1.082***	0.552***	0.972***	0.531***	0.441**	0.144
	(2.77)	(1.60)	(2.61)	(3.98)	(3.03)	(3.08)	(2.97)	(2.07)	(0.99)
Adj. R-sq	0.371	0.353	0.296	0.018	0.019	0.015	0.014	0.013	0.011
N	127165	127165	126731	127152	127152	127165	127165	127165	127158
Late Sample (2011-2021)									
MRF	0.096	-0.029	0.112*	0.047	-0.044	0.056	0.091	-0.035	-0.006
	(0.81)	(-0.34)	(1.75)	(0.28)	(-0.36)	(0.37)	(0.83)	(-0.38)	(-0.08)
Adj. R-sq	0.379	0.311	0.494	0.018	0.020	0.018	0.018	0.014	0.011
N	94548	94548	94548	94538	94538	94548	94548	94548	94548
Early - Late									
	0.395*	0.458	0.236	1.035***	0.596***	0.916***	0.440**	0.476**	0.150
	(1.85)	(1.63)	(1.60)	(3.24)	(2.72)	(2.62)	(2.1)	(2.05)	(0.92)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE	D & S	D & S	D & S	D & S	D & S	D & S	D & S	D & S	D & S

This table reports the results of estimating panel regression in Equation (7) for index incumbents. The full sample includes all incumbent observations in the reconstitution days in the sample period (2000-01, 2021-06). The independent variable is MRF_t^i, the surprise dollar amount of money flowed into stock i at the reconstitution day t (proportional to the previous day's market value) only because of the mechanical change in its weight after the close of the previous trading day. Control variables are log MV (the logarithm of proprietary total market value), IWF (proprietary float factor), β^{CAPM} (loading on the market in the one-factor market model), and the liquidity (average daily turnover of the stock in the previous month). T-statistics based on standard errors double-clustered by stock and day are in parentheses. Significance levels are marked as: $^*p < 0.10; ^{**}p < 0.05; ^{***}p < 0.01$.

value, and momentum risk factors can not justify these stock-specific price movements.

Note that when there is a reconstitution in day t, S&P calculates the weight of the added firm(s) and the new weight of all other index constituents after the close of the day $t-1$ when all close prices (and hence market values) are realized and reports the new weight to all its index feed subscribers including index funds. To minimize their tracking error, index funds try to rebalance their portfolio as close as possible to this time. For a reconstitution at day t, an ideal index fund has two choices: the closing batch auction at day $t-1$ and the opening batch auction at day t. My results also support the conjecture that most trading and price impact are concentrated in these two days. Studying the price changes during the closing batch auction requires intraday data unavailable to the author.

Columns (4) to (6) focus on the cumulative abnormal returns that stock experiences conditional on the (predictable) demand shift that it will experience on the index reconstitution. While column (4) shows that 1% demand shift induces a 40 bps CAR between the announcement and the effective day, columns (5) and (6) show that this abnormal return is almost entirely realized on the effective day and the day before it. This finding is also confirmed in the last column, indicating that the abnormal returns two days before the effective day are insensitive to index funds' rebalancing demand.

The findings mentioned above reassure us about the conjecture that better prices do not incentivize index funds to rebalance their portfolio sooner than the day before the effective day, simply because they are bounded by and compensated for their low tracking error. In fact, no index fund is expected to produce positive investment α, and if it does, it will not be perceived as a positive sign by investors since they expect the index funds to only mirror the index portfolio with close to zero tracking error. Consequently, index funds have no incentive to take the risk of higher tracking error for price gains, and ultimately they are not compensated for such αs. On the contrary, conditional on willingness to follow index guidelines, active investors not bounded by any tracking error will rebalance their portfolios at the announcement since they know they will likely face better prices both for selling deletions and buying additions.

To properly interpret the coefficients, it is crucial to consider the causal implications of the results. MRF is determined based on the values from the day before the effective day, which accurately reflects the actual weight changes before and after index reconstitutions that require rebalancing. However, MRF reveals the magnitude and direction of rebalancing, both foreseeable at the announcement. For instance, if the stock to be added is larger than the stock to be deleted (after float adjustment), MRF will be negative and almost uniform for all incumbents in that particular reconstitution. Note that the majority of the variation in MRF stems from the last ratio in equation (4), which is $Divisor_t/Divisor_{t+1}$. This ratio channels the effect of the discrepancy in the weight of the added and deleted firms into the weights of other index incumbents. Therefore, the market can accurately predict the sign of the effect by comparing the firms' sizes, and the magnitude can be easily estimated using the float-adjusted market value of index incumbents and the deleted stock over the float-adjusted market value of index incumbents and the added stock. Under this high-precision predictability of MRF, regressions with dependent variables that are more than one day before the effective day retain their causal interpretation. In this sense, my findings also contribute to the literature on predictable price pressure, such as Hartzmark and Solomon (2022).

As I will show later in Section 4.2, the price reactions to index additions and deletions have been falling through the years, despite the sharp increase in passive investing that was particularly documented for S&P 500 in Figure 1. The diminishing magnitude of the index effect had been reported in other recent studies, for instance, Bennett et al.

Figure 3: Price impact across time

This figure shows the estimates of price impact across time. Price impact is estimated as the β_t coefficient in the following regression $CAR^*_{jt} = \beta_t MRF^j_t + \phi X_{jt} + \theta_t + \theta_j + \varepsilon_{jt}$, where $\beta_t = \sum_p \beta_p \mathbb{1}(period = p)$ in which the sum goes through division of sample time into two-year periods (2000-01, 2021-06)-eleven periods in total, the last period is one and half years. 95% condence intervals are shown in light shadow around the means.

(2021); Greenwood and Sammon (2022); Patel and Welch (2017) among others. Higher market efficiency fares as the most reasonable explanation for this stark and somewhat surprising observation, but it is not easy to test this hypothesis using the data of index additions and deletions themselves. This is because one can not disentangle easily between decreasing price impact related to the demand-driven component of the index effect or less informative recent index decisions associated with the non-demand-driven part of it. Furthermore, the recent increase in switching between S&P500 stocks and their smaller counterparts, S&P 400 mid-cap and S&P 600 small-cap indices, makes identifying the possible scenarios even harder. The main contribution of this paper is to solve this problem by the novel identification that changes the focus from an information-intensive demand shift on additions and deletions to an information-free demand shift on index incumbents.

To test the hypothesis of flattening demand curves for stocks, I halve the sample of index incumbents into late and early, each containing eleven years of data, and run the same regressions on the two sub-samples. In the earlier sub-sample, all regression results are more substantial, both in size and statistical significance. In the late most coefficients lose their significance and shrink in magnitude. This fact shows that the early part of the sample mostly drove the result in the full sample. Despite the large standard errors in the late sample, the differences in the coefficient estimates between early and late sub-samples are statistically significant in most regressions, which is direct evidence of flattening demand curves beyond index decisions and their informational content. In the shadow of these findings, the shrinking magnitude of the index effect is no more surprising.

I use the dynamic regression setting in Equation (8) with a time-varying coefficient to study the time trend of the price reaction sensitivity to index funds' demand shifts. I use the CAR^{Eff}_{Ann} as the measure of price reaction to index decision to ensure that the outcome variable includes both the anticipated and unanticipated part of the price reaction. This choice is also motivated by the fact that this regression's result will be used in the next section to make predictions for the index effect on additions and deletions, and such a choice of time window ensures an apple-to-apple comparison between the figures.

Figure 3 displays the index funds' price impact estimates using the time-varying model. The graph indicates that the average price impact of index funds' demand has decreased over the last two decades. The sensitivity of prices to demand shifts has dropped from approximately 1.5 in the early part of the sample to nearly zero in the late part. This direct evidence of overall enhancement in market efficiency shows that the market participants, including arbitrageurs and market makers, have greatly improved in providing liquidity to index funds. Moreover, the figure shows that the aggregate price impact is greatly tied to the overall capability of the market in providing liquidity to demand shiftsFor instance, during times of financial crises and the COVID-19 pandemic, when the market was constrained, the price impact multiplier shoots up.

4.1.2 Arbitrage Risk

This section provides a channel to explain the price impact reduction using the arbitrage risk measure introduced in Wurgler and Zhuravskaya (2002). They show that the degree of substitutability of stocks by their close substitutes can explain the cross-section of abnormal returns that those stocks experience in response to demand shifts. I extend their study to see how arbitrage risk has evolved and whether it contributes to explaining the marketwide reduction in price impact.

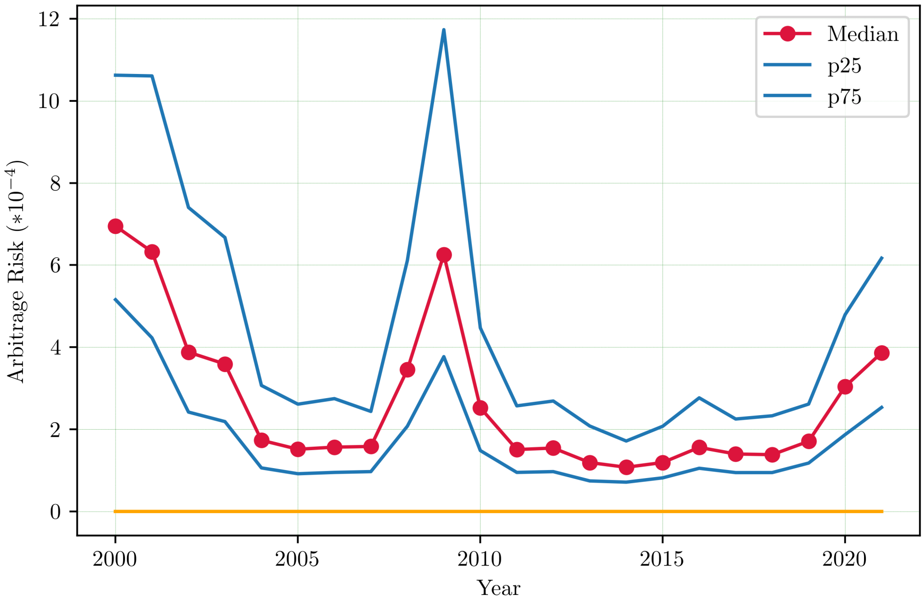
Wurgler and Zhuravskaya (2002) use a measure for arbitrage risk that is the residual of regressing the excess returns of one stock on the excess returns of its substitutes over the calendar day [-365, -20]. I use their first measure (A_1) that incorporates the overall market as the substitute for all stocks. They show that alternative measures of arbitrage risk are highly correlated with this one, and in some cases, they are slightly less informative.

Table 3: MRF and Arbitrage Risk

	(1) CAR_{Ann}^{Eff}	(2) CAR_{Ann}^{Eff}	(3) CAR_{Ann}^{Eff}	(4) CAR_{Ann}^{Eff}	(5) CAR_{Ann}^{Eff}	(6) CAR_{Ann}^{Eff}	(7) CAR_{Ann}^{Eff}	(8) CAR_{Ann}^{Eff}
MRF	0.420**	0.427**	0.037	0.146				
	(2.37)	(2.38)	(0.28)	(1.06)				
A_1^N		0.001***	0.001***	0.001***		0.001***	0.001***	0.001***
		(3.02)	(3.25)	(3.26)		(3.01)	(3.02)	(3.02)
$MRF \times A_1^N$			0.525***	0.548***				
			(5.88)	(5.05)				
$MRF \times A_1^N \times Late$				-0.543**				
				(-2.05)				
$Shockbil$					0.008**	0.008**	-0.000	0.003
					(2.14)	(2.15)	(-0.05)	(0.47)
$Shockbil \times A_1^N$							0.021	0.023
							(1.04)	(1.04)
$Shockbil \times A_1^N \times Late$								-0.020
								(-1.22)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
FE	D & S	D & S	D & S	D & S	D & S	D & S	D & S	D & S
N	221604	221604	221604	221604	221604	221604	221604	221604
Adj. R-sq	0.019	0.019	0.020	0.020	0.019	0.019	0.019	0.019

This table reports the results of estimating panel regression in Equation (7) on index incumbents. The dependent variable in all regressions is the cumulative abnormal returns of index incumbents from the announcement day to the effective day of index reconstitutions. The independent variables include MRF (demand shock in percentage) and $Shockbil$ (demand shock in USD billions). A_1 is the arbitrage risk according to Wurgler and Zhuravskaya (2002). $Late$ is a dummy for the second half of the sample period. Control variables are $\log MV$ (the logarithm of total market value), IWF (proprietary float factor), β^{CAPM} (loading on the market in the one-factor market model). The sample period is (2000-01, 2021-06). T-statistics based on standard errors double-clustered by stock and day are in parentheses. Significance levels are marked as: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 4: Arbitrage risk across time



This figure shows the evolution of stocks' arbitrage risk through time. Arbitrage risk (A_1) is measured according to Wurgler and Zhuravskaya (2002). The red line shows the median of index incumbents' arbitrage risk in each year, and the blue lines show the 25th and 75th percentiles. The sample period is (2000-01, 2021-06).

Table 3 explains the relation between arbitrage risk and price impact. The outcome variable is the total abnormal return of index incumbents between the announcement and the effective day of index changes, inclusive of both dates. Regression (1) is the baseline regression taken from Table 2 brought here for comparison. Regression (1) and (2) show that demand shock size and arbitrage risk are positively and significantly related to event returns. Regression (3) confirms that arbitrage risk is the channel through which demand shocks impact prices; Once I control for the interaction of MRF and arbitrage risk, the coefficient of MRF is no longer significantly different from zero. In other words, if a stock has perfect substitutes (hence, zero arbitrage risk), demand shifts will not impact its price. Regression (4) shows that the association mentioned above still exists in the late part of the sample but to a lesser extent. Specifications (5)-(8) replace the MRF (that is, demand shock in fraction) with the demand shock in currency amount (USD billions). Overall, these specifications show that although both demand shocks in fraction (of total market cap) and demand shocks in dollar amounts contribute to explaining realized abnormal returns, the demand shock in percentage captures the variations in a sharper manner.

While table 3 shows how arbitrage risk acts as a channel between demand shocks and their price impact, Figure 4 complements the picture by demonstrating how this measure has evolved through time. This figure shows that arbitrage risk took a declining trend from 2000 onwards and stabilized at its minimum level for four years before the 2008 financial crisis. The spike of arbitrage risk after the 2008 financial crisis subsided in 2011, and it returned to its minimum level and remained around that level in all the years before the COVID-19 pandemic in 2020. Overall, this figure shows three points: First, arbitrage risk crucially depends on the stability of financial markets. Second, the overall reduction in arbitrage risk, besides the results in Table 3, shows that the reduction in price impact is partially due to improvement in the overall substitutability of stocks for one another. In other words, stocks generally have much closer substitutes in the late part of the sample than in the earlier part, and this reduces the price impact associated with demand shifts. Third, the parallel trend of arbitrage risk and price impact multiplier in Figure 3, including the spikes in 2008 and 2020, reassures that arbitrate risk is channel between demand shift and price changes, and the documented reduction in price impact is indeed due to reduction in arbitrage risk and not just a time trend.

4.1.3 Elasticity of Demand

The price elasticity of index funds' demand can be directly calculated as $-1/\beta$, in which β comes from the price impact estimates in the previous section. With flat or perfectly elastic demand curves, the price elasticity is $-\infty$, and with downward-sloping or imperfectly elastic demand, the price elasticity approaches zero.

Despite the crucial importance of this parameter in asset pricing models, the literature offers a very broad range of its estimates. Wurgler and Zhuravskaya (2002) list a comprehensive review of extant price elasticity estimates, most of which revolve around -5 to -10. For instance, the price elasticity estimate from a cleanly identified study of Kaul et al. (2000) is -10 on a sample of stocks in the Toronto Stock Exchange when the definition of the TSE 300 index for the floating percentage of firms changed. In a recent study, Gabaix and Koijen (2022) lists the most recent estimates of price elasticity of demand. The estimates using individual stocks characteristic like the present paper, as opposed to those using factor level or macro estimates, range between -0.4 to -3.3. While some of these papers use index redefinition such as Pavlova and Sikorskaya (2022) and Chang et al. (2014), there are papers leveraging other demand shifts such as dividend payouts as in Schmickler (2020) and Hartzmark and Solomon (2022), and mutual fund flows in Lou (2012).

The identification of elasticity in the extant literature raises three concerns which are addressed in this paper. Firstly, the inherent problem of estimating the slope of the demand curve, and hence the elasticity of demand for stocks, is that in almost all events that provoke a sizable demand shift, such as index inclusions and exclusions, information can have a role in price reactions. Therefore, the price response in most of the proposed settings combines informational and demand components. Since this information is intrinsically endogenous to the provoked demand and consequently to prices, the elasticity estimates in these studies can be highly confounded. This criticism is mainly leveled at the studies claiming downward-sloping demand curves solely based on the price reactions upon S&P inclusion and exclusions such as Shleifer (1986).

The second concern in estimating elasticity using event studies, such as those on index inclusions and exclusion, is that they only measure the average price impact in response to the average demand. For example, Chang et al. (2014) reaches a price impact of 5% in response to an average demand shift of about 7.3% and concludes with a price elasticity of -1.46. This calculation is correct only if we believe in a homogeneous price impact for stocks. However, many other important factors, such as size, the floating fraction of stock, and the effective supply of shares, may plausibly affect the elasticities. So the average elasticity for stocks may not equate to the negative of average demand over average return. In contrast, in this paper, I directly estimate the individual price impact for infinitesimal individual demand surprises for stocks controlling for individual firm characteristics to lift this issue in estimation.

The last concern in estimating the price elasticity of demand is best described in Pavlova and Sikorskaya (2022). They show that it is essential to control the effective supply of the stocks in estimating the elasticity of demand. Otherwise, the estimates show the demand curve steeper than it is. This concern is particularly relevant in the studies that estimate the price reaction in response to significant demand shifts, such as index inclusion and exclusion. Although very crucial, this concern is not relevant for the setting of this paper since I am using tiny surprises in the weight of index incumbents and not added and deleted firms themselves. Such minor rebalancings do not move the effective supply of the stocks.

Focusing on the daily returns, on the effective days, in the first column of Table 2, the implied price elasticity of demand is -2 for the early sample and -4.2 for the entire sample. Since the price reaction on an effective day does not include the surprise of index decisions on the announcement, it is instructive to see the price elasticity implied by the price reaction for the entire period of announcement to implementation using the CAR_{Ann}^{Eff} in column (4). Focusing on this measure of price changes also has the advantage of abstracting from market movements in finding the average implied price elasticity. Variations in total cumulative abnormal return between the announcement and effective day of index decisions imply a price elasticity of nearly -1 in the early sample and -2.5 in the full sample. These estimates align with the results implied by the time-varying model.

The estimates of elasticity in this section could be called into question if index funds, which incur transaction costs for their trades, do not rebalance their portfolio in response to changes in index composition. Similarly, the possibility that some active funds may trade based on index guidelines biasing the estimates upward can also be a concern. While these are legitimate identification concerns, they should not be overemphasized for two reasons. First, Pavlova and Sikorskaya (2022) have shown that passive funds benchmarked to S&P 500 have almost zero tracking error (0.2-0.4 % per annum) in their entire sample period and have held, on average, 99.6% of their benchmark stocks. This evidence suggests that at least passive funds benchmarked to S&P 500 do exactly as they are expected: They mirror the index portfolio with no discretion.

Second, although some active funds may trade based on index inclusion or exclusion decisions, it is unlikely that they would rebalance other stocks in that benchmark according to updated weights. Moreover, since they don't hold the entire index portfolio, their rebalancing would not be correlated with that of index funds. Lastly, academic literature on the index effect suggests that active funds would trade on the announcement, as they know they can get better prices at that time compared to the effective day. Therefore, even if active funds rebalance their portfolio based on index decisions, they are unlikely to do it in a way that affects the regression results in Table 2. These results show that the effect is concentrated on the effective day and the day before, indicating that they are related to index funds' demand that trade according to the index schedule.

4.1.4 Demand and Liquidity

The weight surprises experienced by index incumbents due to the difference in the weight of added and deleted firms during reconstitutions are indeed relatively small. An example provided in Section A.1 in the Appendix clarifies this point. If the weight of the added firm(s) is 1% more than the weight of the deleted firm(s), all index incumbents will experience a weight reduction of approximately 1% after the event. Considering that the average firm has an index weight of around 0.2%, even in this extreme example, the surprise in the weight of index incumbents would be on the order of 0.002%.

It is important to note that although these surprises may seem diminutive in face value, they can have a significant impact when multiplied by the total assets under the management of index funds. As of 2022, the total assets under the management of index funds are estimated to be around USD 5.4 trillion[16].

This section shows that despite the weight surprises being small in face values, they

[16] Index fact sheet, available on https://www.spglobal.com/spdji/en/indices/equity/sp-500/

Table 4: MRF and turnover

	(1) TO_t	(2) TO_t	(3) TO_t	(4) TO_t	(5) TO_{t-1}	(6) TO_{t-1}	(7) TO_{t-1}	(8) TO_{t-1}
$abs(MRF)$	0.357***	0.201***	0.199***	0.076*	0.973***	0.802***	0.799***	0.123**
	(4.98)	(3.92)	(3.90)	(1.71)	(7.01)	(6.81)	(6.78)	(2.19)
$AvgTO_M$		0.737***	0.737***	0.736***		0.809***	0.809***	0.807***
		(25.76)	(25.75)	(25.59)		(26.03)	(26.02)	(25.91)
$MRF > 0$			0.000	0.000			0.000	0.000
			(1.22)	(1.07)			(0.62)	(0.41)
$Q - AvgTO_M$=1 × $abs(MRF)$				0.000				0.000
				(.)				(.)
$Q - AvgTO_M$=2 × $abs(MRF)$				-0.025				0.048
				(-0.55)				(0.64)
$Q - AvgTO_M$=3 × $abs(MRF)$				0.072				0.570***
				(0.85)				(4.50)
$Q - AvgTO_M$=4 × $abs(MRF)$				0.265**				1.244***
				(2.42)				(5.85)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
FE	D & S	D & S	D & S	D & S	D & S	D & S	D & S	D & S
N	221624	221624	221624	221624	221624	221624	221624	221624
Adj. R-sq	0.440	0.626	0.626	0.626	0.442	0.656	0.656	0.658

This table reports the results of estimating panel regression in Equation (7) for index incumbents when the dependent variable is daily turnover. The sample includes all incumbent observations in the reconstitution days in the sample period (2000-01, 2021-06). The independent variable is the absolute value of MRF_t^i, the surprise dollar amount of money flowed into stock i at the reconstitution day t (proportional to the previous day's market value) only because of the mechanical change in its weight after the close of the previous trading day. Control variables include $\log MV$ (the logarithm of proprietary total market value), IWF (proprietary float factor), and β^{CAPM} (loading on the market in the one-factor market model). T-statistics based on standard errors double-clustered by stock and day are in parentheses. Significance levels are marked as: $^{*}p < 0.10; ^{**}p < 0.05; ^{***}p < 0.01$.

invoke a considerable demand shift on the index incumbents. I use stock turnover, defined as the following equation $T_t^j = vol_t^j / S_t^j$, in which vol_t^j is the daily volume of trades and S_t^j is the number of shares outstanding of stock j in day t, as the dependent variable of the panel regression in Equation (7), and the absolute value of the MRF measure as the independent variable since the direction of index fund activities (buy or sell) has no bearing on the volume of trades. I verify this by adding a dummy of the MRF sign to the regressions.

Estimation results are reported in Table 4. The coefficient estimates of $abs(MRF)$ are around 0.3 and 0.9, respectively, on the effective date and the day before it, and are highly significant. Interestingly, the coefficient change is marginal even when the average of the dependent variable in the previous month is added to the explanatory variables. Regarding economic significance, given the standard deviation of MRF is about 0.083%, one standard deviation increase in MRF results in a 0.1% increase in the stock turnover that is 10% of this variable's sample standard deviation. Regressions (3) and (7) reassure that the direction of index funds' activity (buy or sell) does not have a bearing on the amount of increase in stock turnover, and the effect is symmetric for positive and negative MRF. Regressions (4) and (8) show that the average increase in turnover due to the index funds' rebalancing is mostly concentrated on the most liquid stocks. In untabulated results, I verified that fixed effects and controls only marginally contribute to the findings, especially when I control for the stocks' unconditional liquidity by their average turnover in the preceding month ($AvgTO_m$).

4.1.5 Demand and Volatility

This section the relation between non-fundamental demand shifts and stocks' volatility. For the measure of daily volatility, I use stocks' normalized price range as defined as the following equation

$$Range_{jt} = \frac{P_{jt}^{High} - P_{jt}^{Low}}{P_{j,t-1}^{close}}, \tag{9}$$

that is the difference between high and low prices normalized by the previous day's closing price.

Estimation results are reported in Table 5. The coefficient estimates of $abs(MRF)$ are around 0.4 regardless of the controls and fixed effects. The coefficient only marginally changes when the average of the dependent variable in the previous month is added to the regressors. Regarding economic significance, given the standard deviations of MRF and *Range* are about 0.083% and 2.4% respectively, one standard deviation increase in MRF results in an increase in the daily stock turnover that is 1.3% of this variable's sample

Table 5: MRF and volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Range_t$	$Range_t$	$Range_t$	$Range_t$	$Range_t$	$Range_t$	$Range_t$	$Range_t$
$abs(MRF)$	0.436***	0.359***	0.346***	0.294***	0.405***	0.364***	0.375***	0.229***
	(5.28)	(5.45)	(5.26)	(5.90)	(3.51)	(4.19)	(4.27)	(3.26)
$AvgRange_M$		0.755***	0.755***	0.754***		0.850***	0.850***	0.849***
		(29.80)	(29.80)	(29.75)		(27.82)	(27.88)	(27.80)
$MRF > 0$			0.001**	0.001**			-0.001	-0.001
			(2.53)	(2.43)			(-0.85)	(-0.86)
$Q - AvgRange_M$=1 × $abs(MRF)$				0.000				0.000
				(.)				(.)
$Q - AvgRange_M$=2 × $abs(MRF)$				-0.040				0.035
				(-0.47)				(0.37)
$Q - AvgRange_M$=3 × $abs(MRF)$				0.006				0.092
				(0.05)				(0.55)
$Q - AvgRange_M$=4 × $abs(MRF)$				0.400				0.652*
				(1.32)				(1.83)
Controls	Y	Y	Y	Y	N	N	N	N
FE	D & S	D & S	D & S	D & S	Y	Y	Y	Y
N	221624	221624	221624	221624	221624	221624	221624	221624
Adj. R-sq	0.597	0.677	0.677	0.677	0.260	0.585	0.585	0.585

This table reports the results of estimating panel regression in Equation (7) for index incumbents when the dependent variable is daily volatility, measured as the daily price range (high - low) over the previous day's closing price. The sample includes all incumbent observations in the reconstitution days in the sample period (2000-01, 2021-06). The independent variable is the absolute value of MRF_t^i, the surprise dollar amount of money flowed into stock i at the reconstitution day t (proportional to the previous day's market value) as a result of the mechanical rebalancing of index funds. Control variables include log MV (the logarithm of proprietary total market value), IWF (proprietary float factor), and β^{CAPM} (loading on the market in the one-factor market model). T-statistics based on standard errors double-clustered by stock and day are in parentheses. Significance levels are marked as: *p < 0.10; **p < 0.05; ***p < 0.01.

standard deviation. Regressions (3) and (7) indicate that the direction of index funds' activity (buy or sell) has little bearing on the amount of increase in stock volatility, as the effect is almost symmetric for positive and negative MRF. Regressions (4) and (8) show that the average increase in volatility due to the index funds' rebalancing is mostly concentrated on the most volatile stocks.

There has been a vibrant literature on *excess volatility puzzle* following the outstanding work of Shiller (1981). The excess volatility puzzle is related to the fundamental observation in financial markets that the volatility of asset prices exceeds what can be explained by changes in the underlying fundamentals. Put differently, it refers to the fact that stock prices tend to fluctuate much more than can be justified by changes in the expected dividends or earnings of the firms. Basak and Pavlova (2013) use a theoretical framework to show that index funds can amplify the volatility of the stocks in their benchmark index and aggregate stock market volatility.

Among the empirical works, Ben-David et al. (2018) show that ETFs, which are primarily passive index trackers, increase the volatility of the stocks in their portfolio through a liquidity channel. They show that liquidity shocks can propagate to the underlying securities through the arbitrage channel, and ETFs may increase the nonfundamental volatility of the securities in their baskets. The findings in this section further support the idea that demand shifts that are unrelated to the fundamentals can increase stock price volatility. However, unlike the liquidity channel documented in Ben-David et al. (2018), the increase in volatility here is driven by the direct trades of indexers in an imperfectly efficient market rather than through the arbitrage activity between ETF prices and the underlying baskets' price.

4.2 Index Additions and Deletions

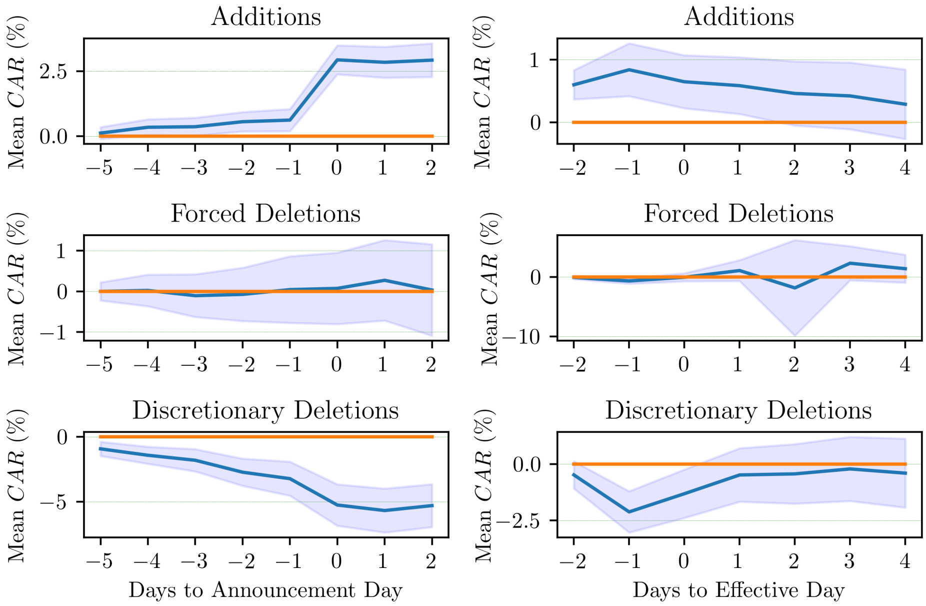
This section studies the short-term price reactions to S&P 500 index reconstitutions. The first part of the section reports the abnormal return of added and deleted firms around the index reconstitution in an event study manner. The second part examines whether index funds' demand can justify the observed effect size by incorporating the estimates of price impact from Section 4.1.

Figures 5 and 6 show the abnormal returns experienced by the added and deleted firms around the event, respectively, in the short and long time windows. The announcement day for each index reconstitution varies in the sample between 1 to 30 trading days before the effective day, with a high mass around the median of 5 trading days[17] which is one calendar week. Therefore, for the long window in Figure 6, I started calculating cumulative abnormal returns from 30 trading days before the effective day of events to ensure announcements happen within the window. Abnormal returns are also summarized numerically in Table 6. All abnormal returns are calculated using coefficients from a four-factor Carhart (1997) model incorporating a moving window of 252 days, conditional on having 100 observations. To avoid contamination of pre-event dates into coefficients, I use coefficients from two weeks (10 trading days) before the effective dates.

For additions, the cumulative abnormal return in the period of $Ann - 30$ to $Ann - 10$ is 1.7% and is significant. The same is true for the period $Ann - 9$ to $Ann - 2$. Between the three dates of announcement day and the days before and after it, only announcement day has a significant return that averages to a whooping amount of 2.3%. The period between announcement day and effective day, including both dates, has an average abnormal return of 2.2%. This is the main figure we know as *index effect* and is

[17]In 60% of events, this distance is between 4 to 6 trading days.

Figure 5: Abnormal returns of index additions and deletions, short CARs



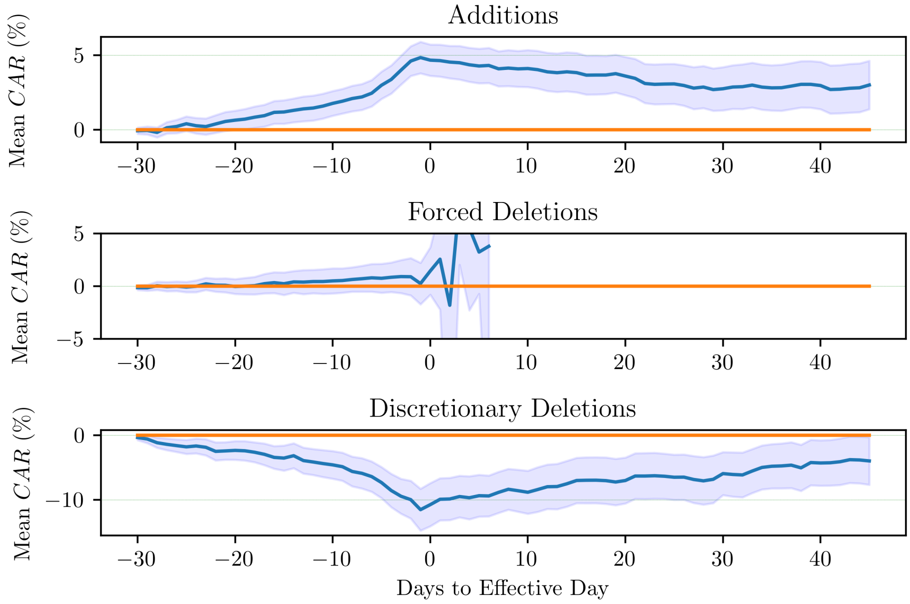
This figure presents the event study results for the abnormal and cumulative abnormal returns of S&P 500 additions and deletions. The sample period is (2000-01, 2021-06). The left figures show the CARs around the announcement day, and the right figures show that around the effective day. Vertical axes report outcomes on percentage return. 95% condence intervals are shown in light shadow around the means.

marked as CAR^* in Table 6. I verify in untabulated results that CAR^*s for additions are not statistically different from the abnormal returns experienced just on the announcement date, so most of the price effects are centered on the announcement. This is also clear when looking at the abnormal returns on the three dates of the effective day, the day before, and after it, which are all small and insignificant for a 95% confidence level. Lastly, the cumulative abnormal returns after the event for all time windows are small and insignificant, which is also confirmed by Figure 6, which shows that the experienced abnormal returns by additions do not revert.

In the analysis, I separate forced and discretionary deletion to emphasize that the forced deletions are in the shadow of more important events than their deletions from the index, which is the reason for their delisting. These abnormal returns are stagnant until a few days before the effective day, but the swings are large in magnitude. So I abstain from commenting on their returns and focus on the discretionary deletions that continue trading after the deletions.

About discretionary deletions, the average CAR in the periods of $Ann - 30$ to $Ann - 10$ and $Ann - 9$ to $Ann - 2$ are both very large and significant summing to about -8.2% although index announcement had not yet happened. This finding shows that the *index*

Figure 6: Abnormal returns of index additions and deletions, long CARs



This figure presents the event study results for the abnormal and cumulative abnormal returns of S&P 500 additions and deletions. The sample period is (2000-01, 2021-06). Horizontal axes show the distance of the dates from the effective day in trading days. Vertical axes report outcomes based on percentage return. The event window begins 30 trading days before the effective day and ends 45 days after. 95% condence intervals are shown in light shadow around the means.

effect is at best responsible for one-third of the trough we observe on Figure 6 on the effective day. These huge negative abnormal returns on discretionary deletions before the announcement are followed by another negative shock on the announcement day for an amount of -2.2%. CAR^* for deletions averages about -2.9%. Similar to additions, the CAR^* for these stocks is not statistically different from the abnormal return just on the announcement. The last trading day before the deletions has a substantial negative average AR of about -1.7% followed by a positive abnormal return on the effective day of about 0.8%.

Deleted stocks experience an upward rally in price after the effective date and exhibit a CAR of about 7% from one day after the effective day up to two months after it (measured as 45 working days). This impressive comeback after the deletions make the average CAR of deletions at the end of the event window statistically indistinguishable from zero at a 95% confidence level. Therefore, unlike additions, the index effect for deletions does not seem permanent.

Two stylized facts observed collectively in Table 6, Figure 5, and Figure 7 are worth mentioning here. First, the CAR^* is substantially smaller in magnitude than the peak CAR in Figure 5 for both additions and discretionary deletions. It means that a sig-

Table 6: Abnormal returns of S&P 500 additions and deletions

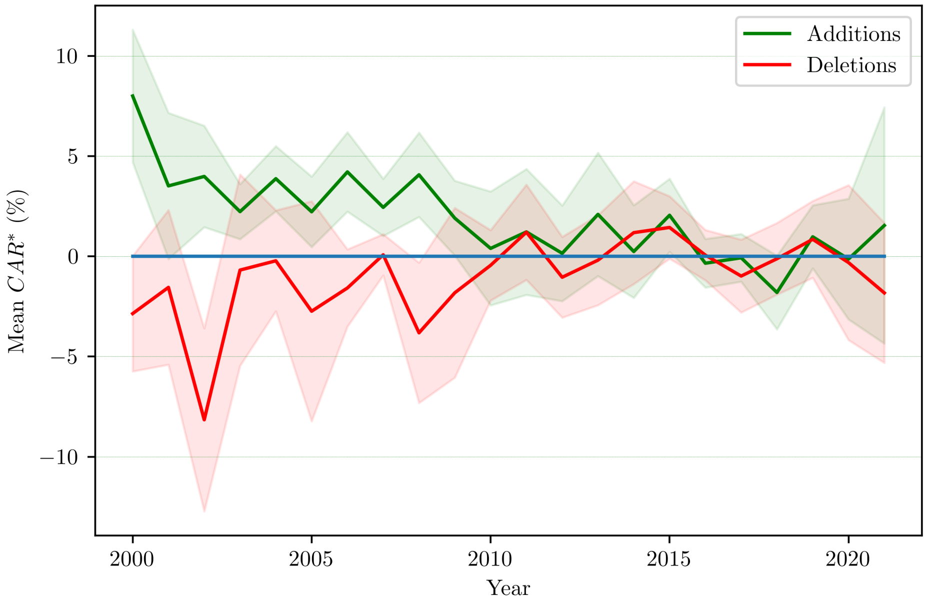
	Additions			Discretionary Deletions			Forced Deletions		
Time/Window	mean	pos (%)	N	mean	pos (%)	N	mean	pos (%)	N
CAR_{Ann-30}^{Ann-10}	1.66***	55.63	453	-4.47***	41.49	241	0.68	60.0	270
	3.57			-4.01			1.06		
CAR_{Ann-9}^{Ann-2}	1.12***	57.76	464	-3.73***	36.78	242	0.04	56.47	278
	3.93			-5.31			0.11		
AR_{Ann-1}	0.07	50.43	464	-0.48	46.69	242	0.14	53.56	267
	0.63			-1.54			0.84		
AR_{Ann}	2.33***	74.35	464	-2.21***	34.17	240	0.04	49.79	241
	13.85			-6.63			0.28		
AR_{Ann+1}	-0.09	46.12	464	-0.42	45.0	240	-0.04	50.23	215
	-0.89			-1.47			-0.26		
$CAR^{*} = CAR_{Ann}^{Eff}$	2.18***	56.06	528	-2.89***	41.56	243	-0.47*	37.77	278
	8.2			-4.88			-1.92		
AR_{Eff-1}	0.23	53.88	464	-1.67***	32.37	241	-0.73***	36.32	212
	1.41			-5.76			-3.57		
AR_{Eff}	-0.19*	47.63	464	0.8**	55.83	240	-1.76	47.83	23
	-1.82			2.59			-1.7		
AR_{Eff+1}	-0.07	50.65	464	0.82***	55.83	240	-0.97	41.67	12
	-0.66			2.71			-0.82		
CAR_{Eff+2}^{Eff+5}	-0.35*	49.24	463	0.34	50.0	238	-	-	0
	-1.8			0.59					
CAR_{Eff+6}^{Eff+10}	-0.19	46.77	464	0.84	52.34	235	-	-	0
	-0.82			1.19					
CAR_{Eff+11}^{Eff+20}	-0.43	50.97	465	1.55**	51.08	231	-	-	0
	-1.48			2.03					

The table presents the event study results for the abnormal and cumulative abnormal returns of S&P 500 additions and deletions. The first column indicates the related window or date. For windows of more than one day, mean cumulative returns are reported in columns (2) and (5), and for other rows that are single dates, the mean abnormal return is shown in those columns. T-statistics for testing whether the mean of the corresponding AR or CAR is statistically different from zero are reported in parentheses. Columns (3) and (6) indicate the percentage of observations with positive abnormal returns. Columns (4) and (7) are the number of observations. Eff and Ann are effective and announcement days, respectively. Significance levels are marked as: *p < 0.10; **p < 0.05; ***p < 0.01.

nificant portion of abnormal returns in peak CARs have been realized before the index announcements, making it implausible to assume that there is information revealed upon the index announcement. If anything, it makes more sense to think index decisions were motivated by these frequent price drifts.

Second, I depict the average CAR^{*}s in different years for additions and discretionary deletions in Figure 7. This figure highlights the seemingly surprising phenomenon that the magnitude of the index effect is decreasing over time despite the sharp increase in the demand of index followers, already documented in Figure 1. This shrinking trend is also noted in Patel and Welch (2017), Bennett et al. (2021), and Greenwood and Sammon

Figure 7: CAR^* of S&P 500 additions and deletions by year



The figure shows the CAR^* of S&P 500 additions (green line) and deletions (red line) by year. The sample period is (2000-01, 2021-06). The horizontal axis shows the corresponding year, and the vertical axis is the average percentage return. The 95% condence intervals are shown in light shadow around the means.

(2022). However, the previous section showed that the price impact multiplier had a decreasing trend over the last decade, independent and beyond index decisions, which can partially explain the shrinking magnitude of the index effect if it happened faster than the increase in passive investing. Given these stylized facts, the rest of this section formally shows that a demand model can adequately replicate the magnitude of the index effect and its decreasing trend.

To provide a benchmark for appropriate price reaction to demand shifts in the absence of information, I use the price impact regressions in Section 4.1 to find the predicted price reaction of index additions and deletions if those events were truly information free and examine if such predictions are in the same magnitude of actual figures. For the model with a time-invariant coefficient estimate, I produce a predicted return ($\hat{Ret_i}$) for each added or deleted stock based on its MRF and the estimates of coefficients in regression (4) of Table 2 whose outcome variable is CAR^*. Regression (4) is chosen since it measures the price reaction precisely on the same time interval for index incumbent that we measure CAR^* on for additions and deletions. I produce the predicted value based on the model with a time-varying coefficient in a similar manner. Crucially, in both models, I incorporate the same controls and fix effects in making the predicted

Table 7: Sample comparison of actual and predicted abnormal returns

Sample	Training Model	$CAR^*_{jt} = \beta MRF^j_t$ $+\phi X_{jt} + \theta_t + \theta_j + \varepsilon_{jt}$		$CAR^*_{jt} = \beta_t MRF^j_t$ $+\phi X_{jt} + \theta_t + \theta_j + \varepsilon_{jt}$	
	Actual	Predicted	Difference	Predicted	Difference
Additions	2.18***	1.77***	0.41	2.35***	-0.17
Discretionary Deletions	-2.89***	-1.75***	-1.14*	-2.32***	-0.57

This table compares the sample means of predicted and actual abnormal returns for additions and discretionary deletions. The model based on which the predictions are made is reported on the top row. Each model is trained on the sample of index incumbents and used on the sample of additions and deletions to make the predicted values. The sample period is (2000-01, 2021-06). Significance levels are marked as: $^{*}p < 0.10; ^{**}p < 0.05; ^{***}p < 0.01$.

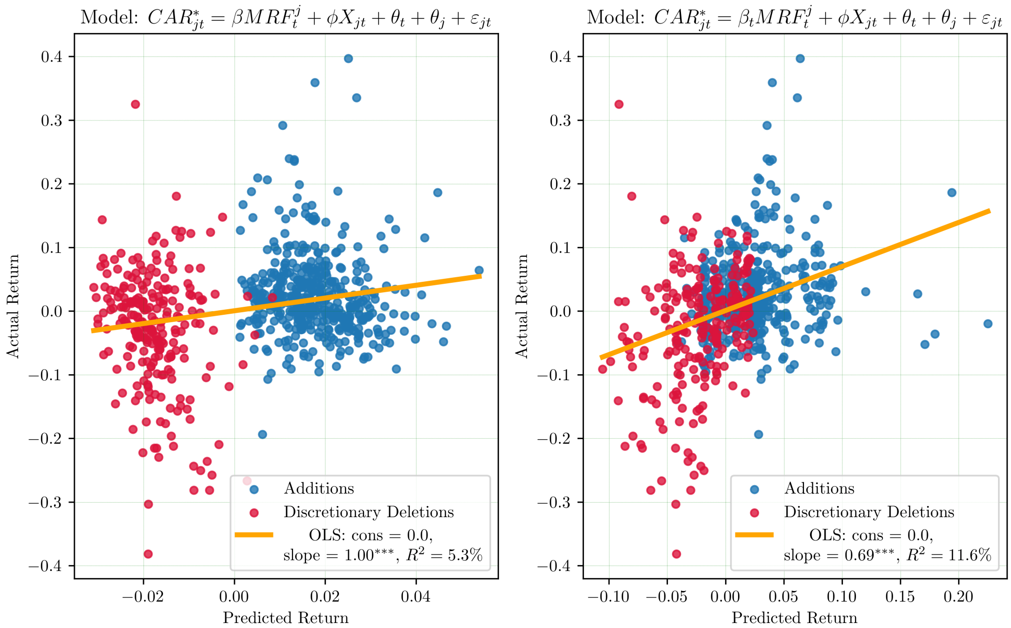
values that were used in the reference estimation. Results of this prediction exercise are presented in Table 7 and Figure 8.

Table 7 indicates that the sample mean of predicted CAR^*s for additions and discretionary deletions and the actual CAR^*s are of a similar order of magnitude. The sample means are statistically indistinguishable at the 95% confidence level for both additions and discretionary deletions in both models. This finding suggests that the demand component is sufficient to explain the magnitude of the abnormal returns observed on S&P 500 additions and deletions. Significantly, these findings do not entirely discount the existence of informational components, such as information, awareness, liquidity, and attention, which may have some impact on the involved stock. Instead, they indicate that if these components do exist, their outcomes must cancel out and leave a negligible net marginal impact on the average magnitude of abnormal returns. This is not farfetched, given the mixed evidence of these components on the stocks. For example, while the effect of improved awareness of market participants is perceived positively for additions in Chen et al. (2004), Bennett et al. (2021) show that the greater scrutiny as a result of heightened attention after the addition of stocks to the S&P 500 has some adverse effects on the firms' performance.

Figure 8 displays a scatter plot of the predicted and actual CAR^*s based on the two models. Each point on the graph represents a stock, with its actual CAR^* on the vertical axis and its predicted value on the horizontal axis. The figure also details the simple line that passes through the points from a univariate OLS regression. In both cases, the intercept is close to zero, which is expected given that Table 7 revealed that the predicted values perfectly capture the sample means. The slope of the lines in both models is close to one and statistically indistinguishable from it in the model with time-invariant coefficients.

Additionally, the figure reports the R^2 of the underlying regressions, which are out-of-sample R^2s by definition since the added and deleted stocks were not included in

Figure 8: Actual and predicted values of CAR^* for S&P 500 additions and deletions



The figure shows the actual cumulative abnormal return of S&P 500 additions and deletions between announcement and effective day (CAR^*) on the vertical axis, and the predicted values of these amount on the horizontal axis. Blue dots represent additions and red dot represent discretionary deletions. In the left figure predicted values are made using a static (time-invariant) model, while in the right figure a dynamic model with time varying sensitivity is used. The orange line shows the OLS regression of actual CAR^*s on the predicted ones. The sample period is (2000-01, 2021-06).

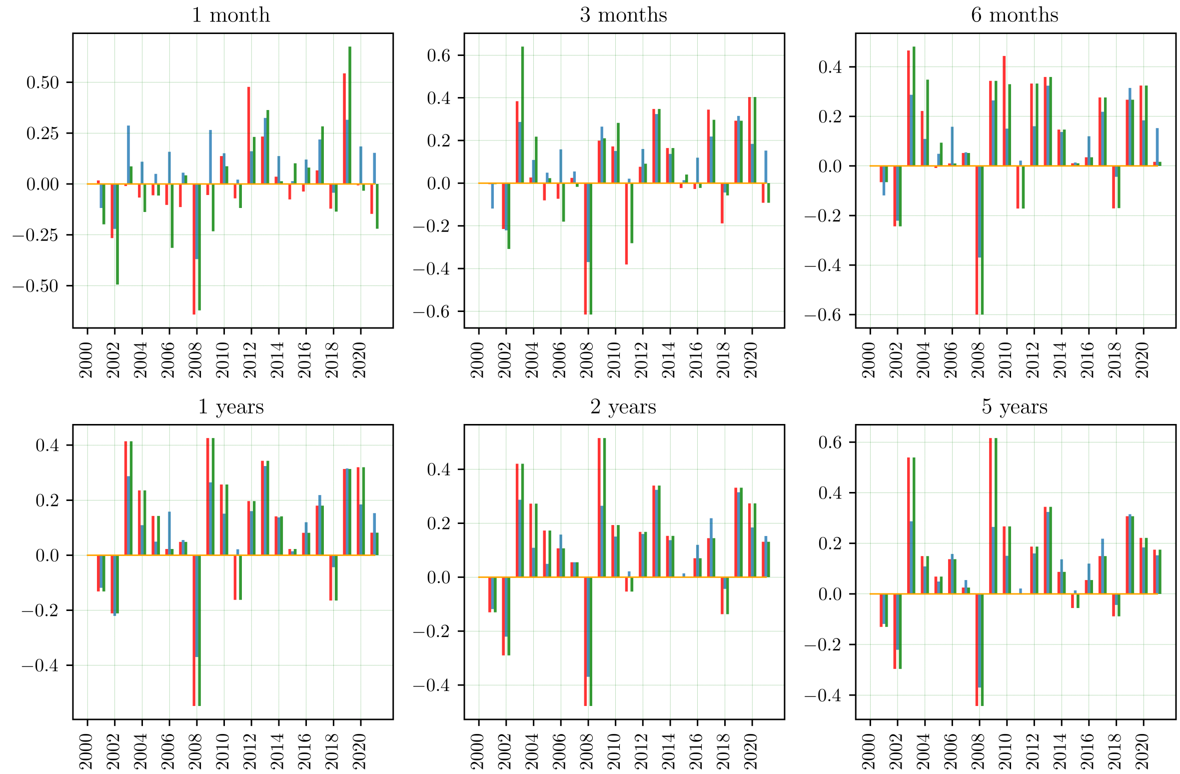
the sample of the training model that was estimated on the index incumbents. The R^2 of the model with time-varying coefficients is slightly higher, as this model more effectively captures the variation in price reactions due to changes in aggregate market conditions. The predictions of the time-varying model have a wider range in which both added and deleted stocks exhibit negative and positive returns, just as in the actual returns. Furthermore, in unreported results, I verified that the dynamic model also captures the decreasing trend of the index effect in the sense that the overall magnitude of the predictions decreases over time.

4.3 Long-term Analysis

4.3.1 Long-term Returns

This section investigates the returns of S&P additions and deletions in longer horizons. The purpose is to determine whether adding a company to the index is a form of reward for

Figure 9: Calendar-time portfolio returns over time



The figure shows the annual returns of the calendar-time portfolios constructed by recently added (green) and recently deleted (red) stocks. The annual return of the S&P 500 total return index (blue) is added as a benchmark. The holding period of the stocks in the portfolios after the event is mentioned above the figures. The sample period is (2000-01, 2021-06).

its past exemplary performance or a reflection of its future potential for success. Similarly, it aims to discern whether removal from the index is a penalty for substandard past performance or a result of inferior prospects. The findings indicate that S&P inclusion and exclusion decisions are more closely linked to a company's past performance and stock returns, thereby doubting the hypothesis that these decisions are based on insider information or superior analytical power. I consider only discretionary deletions in this section since forced deletions don't exist after the event.

To examine long-term returns, I employed calendar-time portfolios due to their ability to account for cross-sectional correlation among constituent stocks within the portfolio, as opposed to CARs. In addition, these portfolios offer a practical investment strategy. I created two groups of equal-weighted portfolios based on recently added and deleted stocks using the following approach: for each holding period of N days, the corresponding portfolios are comprised of stocks added to or removed from the index during the preceding N days. I repeated this strategy for multiple holding periods to identify trends. These portfolios were constructed at the outset of the sample period and rebalanced daily until the end of it. Dividends were reinvested in the corresponding stocks. If a portfolio was empty in a day, its value was kept still until the next time a stock was added to it.

Figure 9 shows each year's annual return of constructed portfolios. S&P 500 total return index is also added to the figures for better comparison. While there are many variations between the added and the deleted portfolios for short holding periods, there is virtually no difference between their returns in longer horizons. Furthermore, in most of the years, the direction of their returns agrees with that of the index.

Table 8 presents a comparison of portfolio returns in a different manner. First, long-horizon portfolios that held assets in them for over a year generated a larger average return than the index. However, their sharp ratios were much lower than that of the index. Second, none of the portfolios, including the index, produced a positive *alpha*. In particular, both portfolios yielded a negative and significant *alpha* for short holding periods. These findings pose evidence against the information hypothesis. Third, Chan et al. (2013) found positive and significant *alpha*s on similar equal-weighted calendar-time portfolios using a sample that predates the one used in this study. Therefore, it appears that even if S&P 500 changes were informative in the past, they are no longer so.

4.3.2 Fundamental Analysis

In this section, I analyze the fundamental characteristics of the stocks added and deleted from the S&P 500 index using an event-study approach. The study uses financial ratios to ensure comparability, with quarter zero representing the last fiscal quarter for which

Table 8: Calendar-time portfolio return characteristics

Portfolio	Holding Period	Mean	STD	Sharpe Ratio	Num Stocks	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	R^2
S&P 500	-	0.67	4.35	0.12	501.46	0.01	0.98***	-0.17***	0.02***	-0.02***	99.51
Additions	1 month	-0.42	8.06	-0.07	2.01	-1.22***	0.94***	0.42***	-0.01	0.09	33.51
Additions	3 months	0.35	7.14	0.03	6.00	-0.57*	1.12***	0.46***	-0.09	0.14**	59.24
Additions	6 months	0.60	6.38	0.07	11.96	-0.28	1.15***	0.32***	-0.16**	0.10**	73.33
Additions	1 year	0.57	6.13	0.07	23.95	-0.25	1.10***	0.34***	-0.28***	-0.05	83.07
Additions	2 years	0.69	6.27	0.09	46.62	-0.12	1.12***	0.32***	-0.26***	-0.15***	86.65
Additions	5 years	0.73	6.52	0.09	105.52	-0.12	1.15***	0.39***	-0.19***	-0.21***	89.24
Deletions	1 month	-0.30	6.18	-0.05	0.88	-0.84**	0.52***	0.40***	-0.00	0.01	23.23
Deletions	3 month	0.12	6.49	-0.00	2.59	-0.68**	0.97***	0.41***	-0.17**	0.06	56.62
Deletions	6 month	0.59	6.31	0.07	5.08	-0.28	1.12***	0.36***	-0.18***	0.09**	73.39
Deletions	1 year	0.61	6.09	0.08	10.02	-0.21	1.09***	0.36***	-0.29***	-0.06*	83.58
Deletions	2 years	0.73	6.23	0.10	18.95	-0.08	1.11***	0.35***	-0.27***	-0.15***	87.13
Deletions	5 years	0.76	6.48	0.10	40.23	-0.08	1.13***	0.41***	-0.20***	-0.22***	89.72

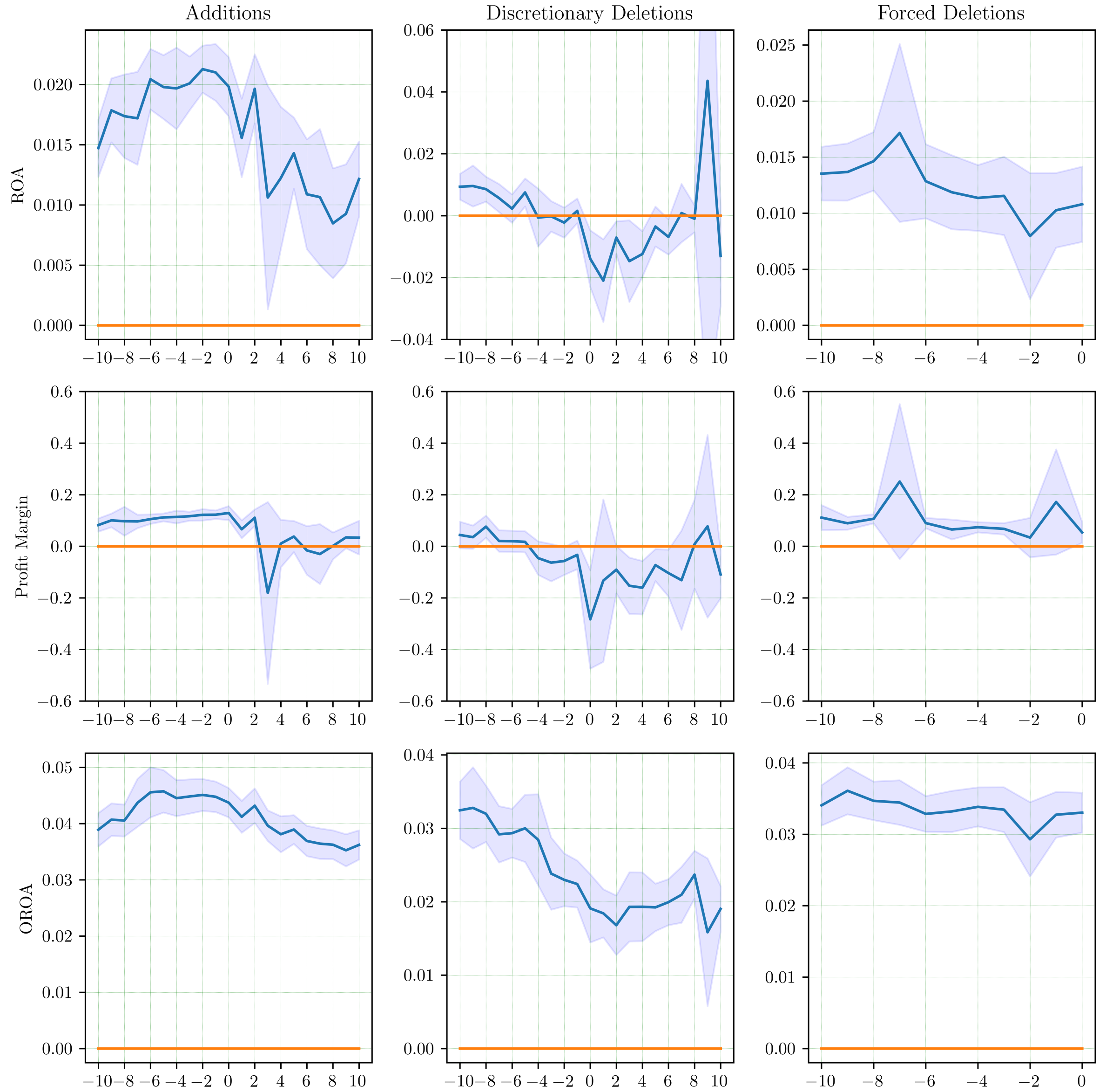
The table compares the monthly returns of the calendar-time portfolio constructed by recently added or deleted stocks. The second column indicates how long each stock is held in the portfolio after the event. Each stock's dividends are reinvested in it, and the first row shows similar measures for the S&P 500 total return index as a benchmark. Columns (3) and (4)) show, respectively, the arithmetic mean and standard deviation of monthly returns. Column (5) measures the Sharpe ratio, defined as the average of monthly excess returns over their standard deviation. Column (6) shows the average number of stocks in the portfolios. Columns (7) to (12) show the results of the regression of monthly returns based on Carhart (1997) four-factor model. The sample period is (2000-01, 2021-06). Significance levels are marked as: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

balance sheet data was available at the time of the index announcement. To measure profitability and efficiency, I consider three key metrics: Return on Assets (ROA), Profit Margin (net income/sales), and Operating ROA (operating income/assets), where operating income is defined as operating income before depreciation, amortization, and taxes, plus interest income.

The event study results shown in Figure 10 reveal that, for all the suggested measures, the S&P 500 additions are at their highest around the time of the index announcement. This result suggests that the index committee selected firms for inclusion when they had recently experienced several quarters of growth, leading to their best recent stance, as reflected in their financial ratios. However, this good performance is not necessarily sustainable and is subject to mean reversion, as all the measures decline right after the inclusion.

Index deletion exhibits an inverse pattern. These firms are deleted from the index right after they report their first negative net income, usually after several quarters of decreasing net income starting approximately two years before the deletion event. Decreasing operating ROA in the third row confirms that the negative net income for these firms is not just a financial figure due to higher interest paid, which is coming from lower operating efficiency. The figure also shows that a similar mean reversion mechanism also

Figure 10: Fundamental trends in index additions and deletions



The figure compares fundamentals in index additions and deletions in a quarterly event study framework. Quarter zero represents the last fiscal quarter for which balance sheet data was available at the index announcement. Confidence intervals are shown in light shadow around the means. Fundamental measures are calculated as ROA = net income/ assets, Profit Margin = net income/ Sales, and OROA = operating income/ assets. The sample period is (2000-01, 2021-06). 95% condence intervals are shown in light shadow around the means.

works for these firms, meaning that after they are deleted from the index at their lowest-ever instance, they start to recover. In five years, most measures are already near their previous average amounts.

On the contrary, the pattern of S&P 500 discretionary deletions is characterized by firms being excluded from the index after reporting a negative net income, preceded by a trend of declining net income over multiple quarters. This decline in net income is not solely attributable to higher interest payments but also reflects decreased operating efficiency, as indicated by declining operating return on assets (ROA). After their removal from the index, these firms tend to experience a mean reversion effect, and most of their measures start to recover, approaching their previous levels. The measures for forced deletions, on the other hand, appear to be relatively unchanged, reassuring that these firms' removal from the index was likely a result of external factors rather than their financial performance.

5 Conclusion

While it is widely acknowledged that changes in index composition can result in significant abnormal returns for the affected stocks, the precise cause of these outcomes has yet to be fully understood. Index composition changes result in massive demand shifts from index followers. Yet, it was unknown if this demand alone could explain the abnormal returns experienced by added and deleted firms or if other factors, such as the revelation of new information, heightened attention towards the stocks or improved awareness about it, or overreaction, played a partial role in these seemingly anomalous stock returns.

This study shows that passive index funds' demand shifts due to their portfolio rebalancing substantially impact stocks' prices, liquidity, and volatility. By focusing on index incumbents instead of actively involved stocks, I measured the price impact and price elasticity of index funds' demand using reduced form estimations on a large sample of stocks without the confounding effect of information. The results indicate that a 1% shift in the index funds' demand, unrelated to information or fundamentals, leads to a significant 40 basis points change in a stock's price between the announcement of stock composition changes and their implementation. From this total, 34 basis points were realized during the last two days before the implementation, where these demand shifts were broadly anticipated. This effect was particularly pronounced in the earlier part of the sample, with an estimated price impact multiplier close to one. These findings show that the demand curves of stocks are flattening over time. This study also shows that this reduction is indebted to a reduction in overall arbitrage risk of stocks due to closer substitutability that makes the market more efficient.

Building on these insights, I have investigated whether demand alone can account for the magnitude of abnormal returns experienced by S&P 500 additions and deletions. My results indicate that the estimates from a demand-driven model trained on the sample of index incumbents are sufficient to predict the magnitude and trend of index effect on additions and deletions, which calls into question the role and net effect of informational factors suggested in prior research.

Finally, by examining the long-term performance of recently added or deleted stocks, I found that additions to the index typically occur when firms are at their best fundamental stance rather than when they have the highest growth potential. Conversely, deletions occur when firms report a negative net income following a trend of declining performance. These results suggest mean reversion in the firms' performance, reject the hypothesis that S&P 500 decisions are made based on insider information or superior analytical power, and show that index decisions are rather retrospective.

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A Appendix

A.1 An example of incumbent weight changes

This section offers a simple example to illustrate the dynamics of index incumbent weight changes when there is a heterogeneity in the weight of added and deleted firm(s). Assume some firm X with a free-float market value of $FFMV_X$ is going to replace firm Y with a free-float market value of $FFMV_Y$ in the composition of S&P 500. Suppose day $t+1$ is the effective day this index reconstitution and the free-float market value of all index incumbents at the close of day t equals $FFMV_{incs}$. Let firm A be a representative index incumbent. Therefore A has already been in the index before the reconstitution and also remains in it afterwards. Table 9 compares the weight and size outcomes before and after the reconstitution.

Table 9: Changes happening in a reconstitution event

	At the close of day t	Before the open of day $t+1$
Constituents	All incumbents + Y	All incumbents + X
Total $FFMV$ of index	$FFMV_{incs} + FFMV_Y$	$FFMV_{incs} + FFMV_X$
w^X	0	$\frac{FFMV_X}{FFMV_{incs}+FFMV_X}$
w^Y	$\frac{FFMV_Y}{FFMV_{incs}+FFMV_Y}$	0
w^A	$\frac{FFMV_A}{FFMV_{incs}+FFMV_Y}$	$\frac{FFMV_A}{FFMV_{incs}+FFMV_X}$

This tables summarises the changes that happen in a reconstitution day. X is a firm that is added to the index in this day, Y is the firm that is dropped from it, and A is an already index constituent than continues to remain in the index list. Dat $t+1$ is the effective day of this reconstitution.

Suppose that the reconstitution results in a 1% increase in the total $FFMV$ of index, that is $(FFMV_{incs} + FFMV_X) = (1.01) * (FFMV_{incs} + FFMV_Y)$. The change in the weight of A will be

$$\Delta w^A_{t+1} = w^A_{\text{before open } t+1} - w^A_{\text{at the close } t} = \frac{FFMV_A}{FFMV_{incs} + FFMV_X} - \frac{FFMV_A}{FFMV_{incs} + FFMV_Y}$$

$$= w^A_{\text{at the close } t}(\frac{1}{1.01} - 1) \simeq (-0.01)w^A_{\text{at the close } t}$$

Therefore, in a nutshell, when a firm is added to the S&P 500 and achieves 1% more weight in the index than the firm it has replaced, all other firms in the index will lose about 1% of their weight in the index after this reconstitution.

Note that since this non-market-driven action has changed the index $FFMV$ overnight, the index divisor will be adjusted to avoid any jump in the index level. In this simple example, index $FFMV$ has increased 1% overnight. So the index divisor will be increased exactly 1% as well. Therefore the last ratio in the equation (4) of Section 2 will be:

$$\frac{Divisor_t}{Divisor_{t+1}} = 0.99$$

and this is precisely the channel through which the difference in the weight of additions and deletions splis over the weight of index incumbents.