Who Clears the Market When Passive Investors Trade?*

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Abstract

We find that firms are the primary sellers of shares when index funds are net buyers, providing shares at a nearly one-for-one rate. Rather than provide liquidity, most demand-side institutions trade in the same direction as index funds, especially over long horizons. To establish causality, we develop a novel instrument for inelastic index fund demand, and show that firms are the most responsive, with prices as the coordinating mechanism. We show evidence consistent with stock compensation as the main source of firm issuance to satisfy passive demand, consistent with firms clearing the market for index fund buying but not selling.

Keywords: Market Clearing, Index Funds, Passive Ownership, Mutual Funds, ETFs, Active Management, Institutional Investors, Price Pressure, Flows, Equity Compensation

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1 Introduction

Passive investors are a unique group, operating differently than most other types of investors: they provide semi-regular flows into index mutual funds and exchange-traded funds (ETFs), who then follow mechanical rules on how to allocate those contributions. This combination of regular flows and mechanical rules suggests that a significant proportion of what index funds buy represents plausibly inelastic demand. Further, as a group, index funds have grown significantly, accumulating ownership of nearly 20% of the U.S. stock market. A foundation of asset markets, however, is market clearing — for every buyer, there must be a seller. In this paper, we ask: When index funds trade, who takes the other side to clear the market? And, more broadly, who has accommodated the rise of passive ownership from 2% to nearly 20% of the market over the last 20 years by selling a significant fraction of the U.S. stock market?

To answer this question, we combine a simple regression framework with a market clearing condition, which allows us to quantify how other types of investors trade relative to index funds. We apply this methodology to quarterly change-in-holdings (from mutual funds and 13F filings) and transaction data for each stock included in at least one major index from 2002 to 2021. From these data, we construct quarterly position changes for several mutually-exclusive groups, designed to account for every share that changes hands. Our groups are Index Funds, Active Funds, Other Funds, Pension Funds, Insurance, Financial Institutions, Insiders, Other, Short Sellers, and Firms. The Other group is a residual group which ensures the market clears (which we know it must). We think of this group as capturing the trades retail investors and small institutions, which are not included in our holdings or transaction data. Throughout the paper, we capitalize our group names to distinguish our specific groups from more common usage of the words – i.e., Active Funds vs. active funds, or Firms vs. firms. It is important to note that our Firms group captures all the ways in which a stock's shares outstanding can change, including not only direct Firm activity through buybacks and seasoned equity offerings (SEOs), but also less direct channels like employee stock compensation and the exercise of warrants and convertible debt. These less direct mechanisms are quantitatively large and account for the majority of the variation in total Firm activity.

For each of our 9 non-Index Fund groups, we construct a variable $q_{i,j,t}$ which captures each group j's position change in stock i in quarter t, in units of stock i's shares outstanding at the beginning of quarter t. We then estimate a series of 9 regressions, one for each group, regressing group j's demand on Index Fund demand ($q_{i,IDX,t}$), or

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,IDX,t} + \varepsilon_{i,j,t}.$$

A positive value of β_j indicates that group j tends to buy when Index Funds buy and sell when Index Funds sell. A negative value means group j tends to trade against Index Funds. Market clearing yields the condition that

$$\sum_j \beta_j = -1.$$

In words, market clearing necessitates that when Index Funds buy 1 pp more of a stock in a quarter, all other groups must have collectively sold 1 pp more of that stock in that quarter.

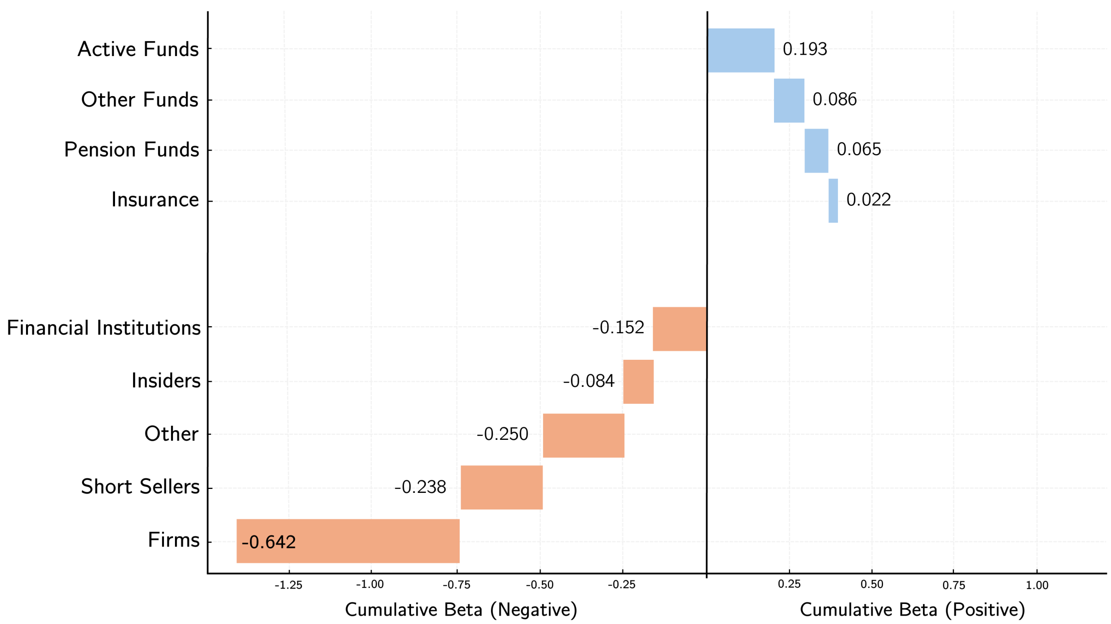
Our main finding is that, for the average passive demand shock, Firms are the most important group in clearing the market. In terms of magnitudes, Firms have a beta of -0.64. That is, when passive investors demand 1 percentage point (pp) of a stock's shares outstanding, Firms take the other side by adjusting the supply of shares by 0.64 pp on average. Figure 1 provides a graphical illustration of who clears the market for the marginal unit of Index Fund demand, i.e., we plot each group's beta. Figure 1 shows that most large demand-side institutions tend to buy and sell in the same direction as Index Funds, based on the positive betas for Active Funds, Other Funds, Pension Funds and Insurance Companies. The lone exception is Financial Institutions, whose negative point estimate of -0.152 suggests a tendency to trade in the opposite direction of Index Funds, though at a rate less than Firms and Short Sellers.[1] Collectively, the supply side – i.e., Firms and Short Sellers – provides 0.88 pp for every 1 pp of Index Fund demand.

The propensity for Firms to take the other side of Index Fund demand is not symmetric with respect to Index Fund buying and selling. Specifically, there is a strong tendency for Firms to provide shares when passive investors are net buyers, but Firms' responses are muted when Index Funds are net sellers. Figure 2 provides a binscatter plot of the net change in shares outstanding (i.e., additional shares supplied or removed from the market by Firms) against the change in holdings by Index Funds, all normalized by shares outstanding at the beginning of each quarter. The overall slope corresponds to our estimate of -0.64, representing how Firms on average take the other side of Index Fund demand. The figure also highlights the asymmetry – in stock-quarters where Index Funds are net purchasers, the estimated slope is -0.95. That is, when Index Funds are net buyers, the market ultimately clears from Firms providing shares at nearly a one-for-one rate.

In fact, in the long run (e.g., on a year-over-year basis), we find that Firms provide shares at more than a one-for-one rate when Index Funds are net buyers. This is possible because when Index Funds buy a stock, large demand-side institutions mimic Index Funds. In fact, large institutions on average tend to buy the same stocks as passive funds to an even greater degree on a year-over-year basis. Large institutions also mimic Index Funds when they are net sellers, both over a quarter and in the long run. So, who then buys when Index Funds are selling? We find that our residual Other group clears the market, nearly on a one-for-one basis. This allows us to add some nuance to market clearing for Index Fund demand: In both the short- and long-run, Firms take the other side of positive passive demand shocks, while small institutions and retail investors take the other side of negative shocks.

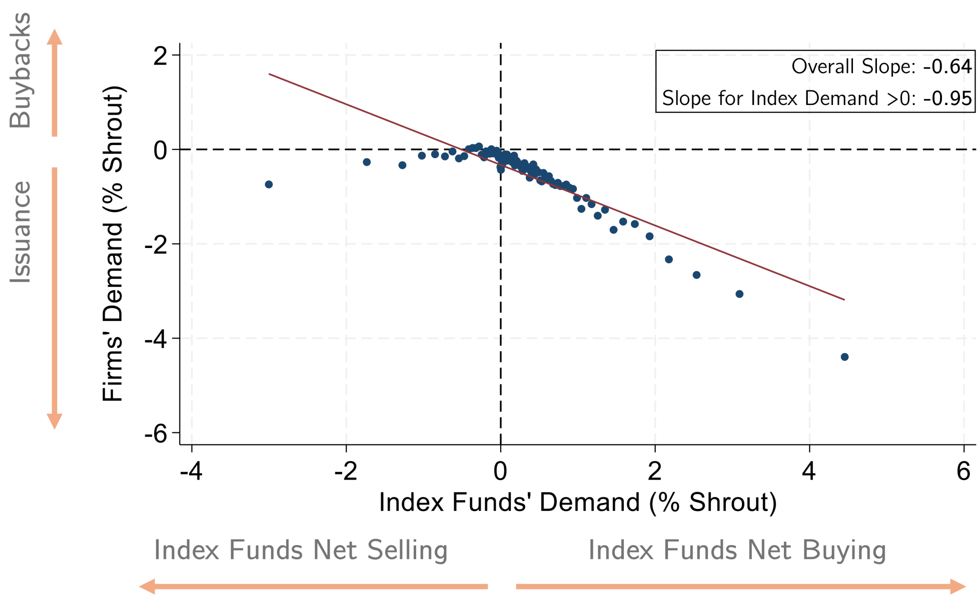
[1] In the long run, e.g., in year-over-year analysis, Financial Institutions trade in the same direction as Index Funds. See 3.2 for more details.

Figure 1: Who Clears the Market for 1 pp of Index Fund Demand?



Notes. We plot how much each of our 9 groups contributes to clear the market per 1 pp of Index Fund demand (i.e., each group's beta in a regression of group demand on Index Fund demand) at the stock-year-quarter level. We provide the beta for each group and collect all positive beta groups on the top half and negative beta groups on the bottom. A group with a positive beta indicates that when Index Funds are net buyers, that group also tends to buy (and vice-versa). A group with a negative beta tends to sell when Index Funds buy and buy when Index Funds sell. See Section 2 for details on the data and methodology. See Section 3 for details on the results.

Figure 2: Firm Demand vs. Index Fund Demand



Notes. We show a binscatter plot of Firm demand against Index Fund demand using stock-year-quarter observations of changes in shares outstanding (Firm demand) and changes in aggregate Index Fund positions in shares (Index Fund demand) between 2002 and 2021. We divide by lagged shares outstanding so the units are in percent ownership of a stock. The binscatter plots divides the observations into 100 equally sized bins and plots the average within each bin. Positive and negative Firm demand represents net buybacks and net issuance, respectively. Positive and negative Index Fund demand represents net buying and selling across all Index Funds. In the legend, we report the slope of a regression of Firm demand on Index Fund demand with all observations (red line) and conditional on Index Fund buying. See Section 2 for details on the data and methodology. See Section 3 for details on the results.

Traditionally with inelastic demand, we think of prices as the mechanism to facilitate market clearing – buyers will push up the price until they can find a willing seller (in our case, Firms). There are alternative stories, however, including an omitted variable (e.g., common fundamental shocks which coordinate Firm and Index Fund demand) and reverse causality (index funds need to mechanically adjust their holdings in response to changes in shares outstanding via, e.g., SEOs and buybacks). We introduce a novel instrument to show that these alternatives are unlikely to be the main drivers of our market clearing facts. We emphasize that our instrumental variables analysis is complimentary to the market clearing analysis described above. That is, regardless who clears the market for exogenous Index Fund demand and what mechanism facilitates the exchange of shares, it does not change the fact that when Index Funds buy more shares, those shares on average come from Firms.

In constructing the instrument for a given stock and quarter, we isolate returns from the subset of stocks that are fundamentally unrelated to the stock in question (the "focal" stock) on the dimensions of industry and characteristics like book-to-market, size, and past-return, but held in the same index fund. We use these unrelated stocks held in the same index fund, which we refer to as the unrelated "co-holdings" of the focal stock, combined with the tendency of index fund investors to chase returns, to identify exogenous index fund buying and selling of the focal stock. The intuition is that if the unrelated co-holdings perform well, the fund will tend to have high returns and index fund investors will chase returns and provide inflows to the fund. The way that nearly all index funds handle flows is to proportionally scale *all* of their holdings up or down (Sammon and Shim, 2023). So, when the index fund receives inflows because of high co-holdings returns, it will buy the focal stock for reasons unrelated to fundamentals of the focal stock. For example, if a fund holds both manufacturing stocks and tech stocks, our instrument will use large, past-winner, growth tech stock returns as an instrument for the demand of a small, past-loser, value manufacturing stock. In the instrumental variables analysis, we also include industry-by-quarter fixed effects to further control for omitted common fundamental shocks, and current and past earnings surprises to control for omitted stock-level fundamental shocks. Combined, our instrument is designed to isolate passive flows unrelated to the focal stock's own performance or fundamentals.

We test two instruments built on this logic and find an estimated Firm beta in response to exogenous Index Fund demand of -0.86 and -0.88, similar to our baseline estimate of -0.64. These magnitudes are in-line with estimates in contemporaneous work by Tamburelli (2024), which uses a sample of S&P 500 additions and a higher-frequency identification strategy to quantify how responsive firms are to inelastic demand shocks. Our tests suggest that an omitted variable and reverse causality are unlikely to be the main drivers our results, and that Firms are responding to price pressure induced by passive demand. In addition, the similarity between our IV and OLS estimates supports the notion that a significant fraction of passive demand is inelastic and/or market clearing for inelastic passive demand is similar to market clearing for *all* passive demand.

Our IV results suggest that prices are the mechanism that facilitates market clearing. To explore this channel more directly, we augment our baseline empirical framework with an indicator for positive excess earnings yield – designed to capture relatively high or low prices(Ben-David and Chinco, 2024). We find that Firms are half as responsive in accommodating passive demand when their excess earnings yield is positive. That is, if prices are not high enough, Firms are significantly less likely to respond and clear the market. This result is not specific to earnings yield, as we find Firms are also less responsive to Index Fund demand when Tobin's Q (i.e., the market-to-book ratio) is low. Further, across all the groups we study, Firms adjust their responsiveness the most based on their relative valuation under either measure. Market clearing, however, must still hold: we find that where valuations are low, Financial Institutions tend play a larger role in accommodating Index Fund Demand. These results provide direct evidence that the price mechanism facilitates Firms' willingness to clear the market for Index Fund demand, and are consistent with the notion of firms acting as arbitrageurs in their own shares.

The responsiveness of Firms to inelastic passive demand then begs the question: What is the source of shares provided by Firms? We decompose Firm demand into contributions from buybacks, SEOs, and a residual Firm demand category that represents compensation and other sources. We find that the compensation/other component of Firm demand accounts for nearly all (more than 80%) of the market clearing activity of Firms. Buybacks and SEOs still contribute to market clearing (in that they have a negative beta) but they play a much smaller role. In addition, we find suggestive evidence that most, if not all, of the residual Firm category comes from stock compensation, using a combination of data on stock compensation expenses from Compustat and scraped data on restricted stock units (RSUs) and employee stock options from 10-K filings, which are not included in Compustat's compensation expense. It is reassuring that changes in shares outstanding from sources other than buybacks and SEOs play a primary role, for two reasons: (1) we know that SEOs are rare and buybacks tend to be somewhat steady, which make each less likely to be the primary drivers of our results, and (2) issuance linked to many sources of compensation represent option-like claims to a company's cash flows that have not yet materialized in the form of shares. That is, employees receive shares and sell them in the market in response to high prices that result from inelastic Index Fund buying, but do not have a built-in mechanism which would lead Firms to buy back shares when prices fall as a result of Index Fund selling. This option-like claim maps nicely to the asymmetric response of Firms to Index Fund demand in Figure 2. This helps elucidate the non-primary-market sources through which Firms can provide a significant quantity of shares in a timely manner.

Contributions and Implications

Our paper's first major contribution is to establish a new fact: Firms are the single largest group in accommodating Index Fund demand, both on average and on the margin.[2] This helps explain how the growth of passive index funds from just above 0% ownership of U.S. equities to nearly 20% is compatible with large institutions having little to no change in asset allocation to equities.

Another contribution of our paper is our novel instrumental variables (IV) setup, designed to identify plausibly exogenous shocks to passive demand. Our IV is much broader than past methods of identifying passive demand shocks using index additions and deletions – which make up less than 2% of firm-quarter observations in our sample. By instead leveraging passive buying and selling driven by flows, we are able to construct demand shocks that span (almost) all stocks and year-quarters. Further, through our instrumental variables design, we establish that the inelastic and plausibly exogenous part of passive demand is proportional to overall passive demand.

Our IV analysis also speaks to who responds to inelastic demand shocks *in general*, not just shocks from passive investors. One way to interpret our IV results is that we identify a meaningful source of inelastic demand shocks given the way that a specific type of investment vehicle – the index fund – deploys flows. That is, we use index funds as a laboratory to better understand inelastic demand shocks in general. In addition, since our results point towards prices as a coordinating device, our results can be extended to any inelastic demand shock that has an impact on prices. Our findings suggest that firms themselves are the most responsive to positive inelastic demand shocks, and no large institutional investor systematically responds to negative inelastic demand shocks, leaving small institutions and/or retail investors to buy the shares.[3]

In addition, our findings establish that Firms are not just issuers of overvalued shares, but are the *marginal provider* of shares when Index Fund demand and overvalued shares coincide. Moreover, our results on prices as the market clearing mechanism suggests an indirect flow of capital from passive investors to companies through Index Funds and secondary financial markets.

On Demand-System Asset Pricing Models Our results suggest that Firms have an upward sloping supply curve. These results have implications for demand-system models in asset pricing (e.g., papers that build from (Koijen and Yogo, 2019)), which often assume the supply of shares is fixed. Extending these models to incorporate Firms as an elastic supplier of shares may add

[2] This is a statement about the equal-weighted average stock-year-quarter. As a group, Firms have bought back shares on net in dollar terms over the past 20 years. Over this same period, Index Funds were also net dollar buyers of shares. Therefore, Firms cannot have cleared the market for *average* passive demand on a value-weighted or dollar basis. Still, for the *marginal* unit of passive demand, even on a value-weighted basis, we find that Firms remain the most responsive group. See Section 3.3.1 and Appendix B.3 for more details.

[3] In quarterly results, we find that our Other group and Financial Institutions contribute the most to market clearing when Index Funds are net sellers. However, in year-over-year analysis, the market clears almost completely from our residual Other group – in the long run, Financial Institutions ultimately sell alongside Index Funds.

an important dimension to this burgeoning literature. The demand-system perspective also helps bring our market clearing exercise full circle – if it were not for Firms responding to passive demand, prices may have risen much more over our sample to facilitate market clearing from less responsive groups.

On the Frequency and Sources of Firm Issuance Our paper documents that Firms not only issue frequently, adding and updating the work of Fama and French (2005), but the source of issuance comes in large part from channels related to employee compensation. Given that this form of issuance often has an option-like structure, it shows that a significant proportion of labor income (and, more specifically, skilled labor income) can be tied to positive demand shocks. In addition, we find that Firms' responsiveness to Index Fund demand shocks has been increasing over the past 20 years. The increase in Firms' responsiveness over time points to greater utilization of, for example, restricted stock and stock options as a form of compensation.

On Capital Structure and Financial Constraints One of the most direct implications of our findings is that positive demand shocks may lead to changes in capital structure. What firms do with the proceeds of issuance, e.g., pay down debt or increase investment, has implications for corporate finance and capital structure policy. Our paper also speaks to financial constraints. Several papers have found that a significant fraction of U.S. companies are constrained from issuing equity through traditional channels like Seasoned Equity Offerings (e.g., Farre-Mensa et al. (2022)). Our findings highlight a way that firms can circumvent restrictions imposed through traditional capital raising channels by substituting traditional sources of compensation for future stock compensation. This allows constrained companies to effectively raise cash by substituting payment to employees today for conditional equity issuance in the future.

Related Literature

Our work is related to several areas of research in asset pricing and corporate finance. First, an old literature has argued that demand shocks unrelated to fundamentals should have no effect on prices (Scholes, 1972). More recent evidence, however, suggests that even non-fundamental demand shocks are crucial for explaining asset price fluctuations (Koijen and Yogo, 2019; Gabaix and Koijen, 2021). We uncover an important part of the story, identifying which groups are on the other side of every passive demand shock over the past 20 years. Our findings add to a growing literature showing that the elasticity of investors who provide liquidity to passive demand and investor heterogeneity matters for asset prices (Van der Beck, 2021; Haddad et al., 2022; Balasubramaniam et al., 2023). In these papers, however, the supply of shares is not endogenized, i.e., the firm and short sellers are not modeled as being responsive to prices. We show that neglecting the role of the firm (and the whole supply side) in market clearing – especially in the case of net buying by passive index funds and ETFs – omits a potentially central player in these demand systems.

In addition, our finding that firms are the ones that clear the market in the face of passive demand has implications for corporate finance. Fama and French (2005) find that issuance is large and very common. Past literature has also shown that firms tend to issue equity when they think their equity is overvalued (Loughran and Ritter, 1995; Graham and Harvey, 2001; Baker and Wurgler, 2002), substitute between debt and equity depending on their relative valuations (Ma, 2019), and issue debt at specific maturities in response to maturity gaps in government debt (Greenwood et al., 2010). Closer to our work, Frazzini and Lamont (2008) argue that mutual fund inflows are a function of investor sentiment, and show that firms in high-inflow funds' portfolios tend to issue equity. We add to this evidence, showing that firms respond not just to information about future fundamentals (e.g., revenue and earnings), but also to inelastic demand and price pressure. These findings have broader implications for the real effects of passive ownership, including its influence on capital structure and payout policy.

Our work is also related to the literature that connects the growth in passive ownership with company buybacks and issuance. Brav et al. (2024) study the growth of institutional ownership by the "Big Three" institutions that primarily offer passive investment vehicles, and they touch on topics including flows, fees, and how firm activity itself can affect passive growth.

More broadly, our paper contributes to a large literature on the effects of inelastic demand by passive funds. Many papers have focused on changes in index membership (see, e.g., Madhavan (2003), Petajisto (2011), Chang et al. (2015), Coles et al. (2022), Van der Beck (2021)), which while important, account for a relatively small share of total trading by passive investors. In this paper, we develop a methodology to study every stock-level quarter-over-quarter change in passive ownership. Importantly, we show that the process for market clearing around index changes is not representative of the average way the market accommodates demand from passive investors. This suggests that the results from studies focused on index changes may not generalize to buying and selling by passive funds in response to flows, which are the predominant source of dollar buying and selling by passive funds.

Perhaps the most closely related paper to ours from a methodological perspective is McLean et al. (2020), who also conduct a market clearing exercise, examining the changes in holdings by 9 groups of investors. Their paper, however, is focused on the implications for return predictability. Specifically, they aim to understand whether any particular group's buying/selling is related to future expected returns and anomalies. Similarly, Ince and Kadlec (2022) aim to understand how the performance of institutional investors is related to who takes the other side of a given trade. In assigning trades to counterparties, Ince and Kadlec (2022) also construct mutually exclusive groups, including issuance/buybacks by firms. They find that much of the decline in institutional investors' performance can be attributed to trades where insiders and firms are on the other side. Unlike these papers, which are focused on return predictability and investment returns, our focus is instead on the market clearing itself. We show which investors are likely to take the other side of trades with passive ownership – and how this may vary depending on the direction of passive trading, the reason for passive trading and across time.

Also closely related are two papers that directly study the connection between passive investment vehicles and equity issuance. Contemporaneous work by Tamburelli (2024) studies the effect of index-tracker demand on firms' behavior in the context of S&P 500 additions. Leveraging daily-frequency variation and identification, Tamburelli (2024) finds that firms are the most important provider of shares to S&P 500 trackers in the immediate wake of index additions. Evans et al. (2023) find that greater ETF ownership increases the probability of an SEO. We believe these papers compliment our broader approach, where Firms emerge as the single-most important group in clearing the market for all sources of passive demand.

Finally, our paper speaks to the importance of employee compensation as a source of changes in shares outstanding. While seasoned equity offerings (SEOs) and buybacks are salient ways firms can adjust shares outstanding, we find that these two channels collectively make up roughly 20% of the way firms respond to passive demand. Our findings suggest that compensation via stock grants and options is by far the largest component of firm activity, but also that those shares ultimately end up in the hands of passive investors. These results have implications for a wide range of topics, including labor shares and income inequality (Eisfeldt et al., 2023a).

2 Data & Empirical Methodology

In this section, we outline the data sources we use. We then describe how we construct our mutually-exclusive "investor" groups, for which we will estimate buying or selling aggregated at the group level for each stock in each quarter. Lastly, we provide our empirical regression methodology to document who clears the market when passive investors buy or sell.

2.1 Data

We outline each of our data sources below and highlight some data cleaning decisions. Appendix A.1 contains a detailed description of the data and our data cleaning steps.

Mutual Fund Holdings Data We use the Thomson Reuters S12 data for quarterly holdings in individual stocks of mutual funds, exchange-traded funds (ETFs), closed-end funds, and unit investment trusts. We separate all funds into three categories: index (passive), active, and other. We classify a fund as an index fund based on the index fund flag and the fund name in the CRSP mutual fund database using the method in Appel et al. (2016). We classify a fund as active if it is in the universe of funds that can be linked between the CRSP mutual fund and Thomson S12 datasets using the WRDS MF links database but it is not otherwise classified as passive. Any remaining funds that cannot be matched between Thompson and CRSP are what constitute our "other funds" group. As discussed in Sammon and Shim (2023), the prevalence of stale filings can create problems when working with changes in holdings. To address this issue, we linearly interpolate holdings of each stock at the fund level across stale quarters, for up to 3 quarters.

Institutional Holdings Data We obtain data on institutional investors' holdings from 13F filings recorded in the Thomson Reuters S34 dataset. Institutions are required to file a 13F if they hold more than $100M in qualified securities. To classify institutional investors into groups, we use the 13F classification procedure in Bushee (2001), and data for the classification from Brian Bushee's website. The classification assigns each institution to one of the following categories: banks, investment companies, independent investment advisors, insurance companies, corporate pension funds, public pension funds, university and foundation endowments, and miscellaneous.

Importantly, the 13F data only contains information on institutions' long positions. While many institutions also have short positions, such data is not reported in the 13F filings. As we describe below, we separately account for changes in short interest – treating it as its own investor group.

Stock Data We use the CRSP monthly stock dataset for data on shares outstanding. While shares outstanding is not traditionally an "investor" category, to completely account for all sources of share changes, we also include the firm itself, which can issue or buy back shares. We identify net share issuance/buybacks based on changes in split-adjusted shares outstanding. Importantly, CRSP shares outstanding does not include treasury or authorized shares.[4] This means that if stock awards have been approved by the board of directors and shares have been authorized – but are held in the firm's treasury stock – those shares will not be counted toward shares outstanding. These shares will only affect net issuance when they are actually awarded to employees and, thus, available in the market if those employees choose to sell shares.

A concern in our setting is that the shares outstanding data in CRSP can be stale – and therefore we may be mismeasuring the timing of Firms' net issuance. We have three robustness checks to ensure that potentially stale shares outstanding data is not driving our findings. First, we also obtained shares outstanding data from FactSet – which uses data from SEC filings to retroactively update shares outstanding data based on when the change actually occurred – and found nearly identical results. Second, we restricted our analysis to Nasdaq-listed stocks, where we are confident the data is not stale, and again observed similar results.[5] Finally, in Section 3.2, we examine net

[4]See the CRSP US Stock Data Description Guide (page 125) for more details.

[5]According to CRSP, shares outstanding data for stocks primarily listed on Nasdaq (CRSP exchange code 3) is updated daily, based on data directly from Nasdaq itself. But, for stocks primarily listed on other exchanges (e.g., those listed on the NYSE), shares outstanding data may only be updated monthly or quarterly.

issuance at longer horizons, which should be less susceptible to stale data concerns, and again find our results are qualitatively unchanged.

Short Interest Data We use short interest data from Compustat following the method in Hanson and Sunderam (2014). We find that the short interest ratio computed using Compustat data is highly correlated with the short interest ratio reported by S&P Global's Markit database. In Appendix C.4, we obtain data from Markit on the shares available for shorting, utilization rates, and shorting costs for robustness tests.

Insider Transactions Data We use the Thomson Reuters Insiders dataset for changes in holdings for company insider transactions, which we aggregate to the stock and quarter level.

Index Constituents Data We obtain S&P 500 and S&P 1500 membership data directly from S&P, while we get data on S&P MidCap 400 and S&P SmallCap 600 membership from Siblis Research. The data from S&P data starts in 2002 and ends in 2021. We also use data from Siblis research to determine Nasdaq 100 membership, which is available from 2015 to 2021. Russell index membership data is obtained directly from FTSE Russell, and runs from 2009 to 2021. Finally, CRSP index membership is provided directly by CRSP, and runs from 2015 to 2021.

Data Filters Our main analyses study the period 2002 to 2021. To be included in our sample, stocks must pass several filters. First, we only include ordinary common shares (CRSP share codes 10-11) traded on major exchanges (CRSP exchange codes 1-3). Second, we exclude stocks that are an acquiring CRSP Permno or have an acquiring CSRP Permno in either quarter t or quarter $t-1$. In such quarters, there can be large changes in split-adjusted shares outstanding, which can create extreme outliers in company issuance activity. We require that each stock is included in one of the major index families (S&P 1500, Russell 3000 or CRSP Total Market) in quarter t, $t-1$ or $t+1$, because our primary objective is to study market clearing when index funds trade.

2.2 Investor Groups

We describe how we use the data described in Section 2.1 to measure position changes for each investor group in each stock and quarter. We first discuss how we address potentially overlapping data (e.g., the same shares being reported both in S12 and 13F filings), then we describe how we construct our investor groups.

Note that throughout the paper we capitalize the name of each of the groups we define below. We do this because many group names are also common finance-related words, so we use capitalization to distinguish our specific group to more common usage of the word (e.g., Insurance vs. insurance).

2.2.1 Eliminating Overlapping Groups

Nearly all mutual funds and ETFs from the S12 mutual fund holdings data are under the umbrella of some financial institution that also files a 13F. This means that mutual fund holdings and 13F holdings have significant overlap. We address this overlap by first identifying all of the 13F institution categories that could include mutual fund holdings in their filings: banks, investment companies, independent investment advisors, and miscellaneous. We then combine the holdings of these four 13F categories together into a single category and subtract all S12 holdings. The remaining holdings form a single category that represents financial institutions excluding fund holdings. This is done for each stock in each quarter.

We see this as a conservative way to avoid double counting the holdings of mutual funds and other funds. We think of the holdings of these financial institutions excluding mutual funds as representing the holdings of hedge funds, large family offices, the proprietary arms of banks, and other large institutional investors.

2.2.2 Constructing Groups

We form 10 mutually exclusive groups. The first set of investor groups comes directly from holdings data, where we can observe quarter-over-quarter changes in holdings per stock, aggregated within group. We use mutual fund and ETF holdings to form the first three groups: Index Funds, Active Funds, and Other Funds (which are the funds in the Thomson Reuters S12 dataset that cannot be matched with the CRSP mutual fund dataset). Throughout the paper, we will often use the term "passive investors" when describing the aggregate Index Fund group.

We use 13F holdings to form three other groups: Insurance (which combines insurance companies and university & foundation endowments), Pension Funds (which combines corporate and public pension plans), and Financial Institutions.[6]

For each of these groups, we measure the net buying or selling for a group in each stock and in each quarter by aggregating (split-adjusted) shares held at the stock and quarter level across all investors within a certain group. We then examine changes in holdings at the stock and quarter level for each group and normalize by shares outstanding in the previous quarter. This gives the aggregate buying or selling activity for a group in a stock-quarter, measured as percent ownership

[6]We combine insurance companies and university & foundation endowments because they are both very long-horizon investors and because the endowments group is relatively small. We also combine corporate and public pension plans because they have common objectives. Financial Institutions excludes all fund holdings, as described in Section 2.1, to avoid double counting.

of a company. We define $q_{i,j,t}$ to capture the aggregate buying or selling activity, and is given by

$$q_{i,j,t} = 100 \cdot \frac{shares_{i,j,t} - shares_{i,j,t-1}}{shrout_{i,t-1}}, \tag{1}$$

where $shares_{i,j,t}$ is the adjusted shares held in stock i by group j in quarter t and $shrout_{i,j,t-1}$ is the shares outstanding in stock i in quarter $t-1$.

As an example using our Index Fund group, if some index funds and ETFs buy shares in a particular stock-quarter and many other index funds and ETFs sell shares, the Index Fund group buying/selling $q_{i,j,t}$ captures net buying or selling across all index funds and ETFs. If there is some imbalance within the Index Fund group, one or more other investor groups collectively must have an imbalance of the opposite sign to clear the market.

The next investor group we measure is Insiders. We do not have data on insider holdings. Instead, we use insider buys and sells to record aggregated insider transactions at the stock-quarter level. For insiders, we have

$$q_{i,Insiders,t} = 100 \cdot \frac{\sum_{i,t} insiderbuys_{i,t} - \sum_{i,t} insidersales_{i,t}}{shrout_{i,t-1}}, \tag{2}$$

where $insiderbuys_{i,t}$ and $insidersales_{i,t}$ are individual insider transactions in split-adjusted shares.

The next two groups account for possible changes in the supply of available shares in the market. The most direct way for the supply of shares to change is for the firm itself to either issue shares or buy back shares. For example, if Index Funds buy 1,000,000 shares of a stock and no other groups trade, it is possible that the firm issues 1,000,000 additional shares, which allows the market to clear. We label this group "Firm," and use changes in shares outstanding as one measure of changes in the number of available shares, or

$$q_{i,Firm,t} = 100 \cdot \frac{shrout_{i,t-1} - shrout_{i,t}}{shrout_{i,t-1}}. \tag{3}$$

For consistency with other groups, we represent Firm issuance as "selling" (i.e., negative changes), which would require that another group buys in order to clear the market. We similarly label buybacks as Firm "buying". Note that $q_{i,Firm,t}$ is an *all-in* measure of (net) issuance, and includes increases in shares outstanding not just from seasoned equity offerings (SEOs) but also from the exercise of warrants/convertible debt, as well as shares issued for employee/executive compensation (Daniel and Titman, 2006; Pontiff and Woodgate, 2009).

The supply of shares can also change through increases in short interest. If an index fund buys 1,000,000 shares and no other groups adjust their positions (including the Firm), a hedge fund or another institution may sell shares short by borrowing from existing holders. For the purposes of market clearing, the accounting of shares is similar for short selling and Firm issuance. We label this group "Short Sellers," and use changes in short interest as a measure of this group's buying and selling, or

$$q_{i,ShortSellers,t} = 100 \cdot \frac{shortinterest_{i,t-1} - shortinterest_{i,t}}{shrout_{i,t-1}}. \tag{4}$$

Short Sellers' position changes are signed just like all other groups – Short Sellers' buying corresponds to decreases in short interest, and selling corresponds to increases in short interest. It is also important to note that many 13F institutions, especially our Financial Institutions group, are likely to be short sellers. However, 13F holdings only capture ownership. One way to think about our Short Sellers group is that it is separating all groups' short positions from their long positions.

We list our 10 groups in Figure 3. The first 9 groups provide a careful accounting of all of the ways in which shares can change hands in the data. However, we know that our data are incomplete and do not account for the ownership of every share of every stock. A nontrivial fraction of holdings, and thus of share changes, will be missed because of the omission of retail investors and institutions that are too small to file 13Fs, as well as other groups we cannot measure directly. Because we know that the market must clear, we attribute the remainder of share changes to a group that we call "Other" to ensure that the market clears. That is, if the first 9 groups above collectively are net purchasers, then it must be that our Other group is a net seller for exactly the same number of shares. This residual Other group is the 10th and final group. For more details on how our Other group is constructed, see Appendix A.2.

The Other group can still be economically relevant in that it can accurately capture the economic activity of small investors. For example, one type of investor that must reside in this category is retail. Although we do not claim that our Other category is a direct quantification of total retail trading activity, we do find that our Other category's position changes are correlated with proxies of net buying and selling by retail investors. We document these patterns in Appendix A.2.3.

Since the Other group guarantees market clearing, it may also be affected by data errors. For example, if there is an erroneous position change in the Pension Funds group, this error will force the residual Other group to take the opposite position to clear the market. We will keep this in mind when assessing the empirical results and conduct analyses that try to assess the degree to which this group captures economic activity or data errors.

2.2.3 Outliers

We trim outliers in each group below the 0.5 percentile and above the 99.5 percentile in our data. That is, we simply delete stock-quarter observations if any one of our groups has a percentage share change that is in the extreme tails of that group's percentage position change distribution. Of course, it is possible that some groups drastically change their positions and that this filter erroneously deletes "true" observations from our dataset. However, we suspect that many of these

Figure 3: Investor Groups

- Mutual Funds
    1. **<u>Index Funds</u>**: Passively-managed index funds
    2. **<u>Active Funds</u>**: Actively-managed funds
    3. **<u>Other Funds</u>**: Funds which cannot be linked between Thompson S12 and the CRSP Mutual Fund data
- 13F Institutions
    4. **<u>Financial Institutions</u>**: All financial institutions excluding mutual fund holdings
    5. **<u>Insurance</u>**: Insurance and endowments
    6. **<u>Pension Funds</u>**: Corporate and public pension funds
- Share Suppliers
    7. **<u>Firms</u>**: Share buybacks and issuance
    8. **<u>Short Sellers</u>**: Changes in the effective supply of shares from either increases in short interest or short covering
- Miscellaneous
    9. **<u>Insiders</u>**: Company insiders required to disclose share transactions
    10. **<u>Other</u>**: Retail, foreign institutions, small institutions and other groups we cannot measure directly. A residual category to enforce market clearing

Notes. This figure enumerates the mutually exclusive investor groups in our data.

outliers come from data errors in the underlying holdings data.[7] In addition, the magnitudes for a subset of the data for some groups are improbably large, even after correcting issues with stale data as described in Section 2.1.

If the outliers are the result of data errors, replacing them with the 0.5 or 99.5 percentile values – i.e., Winsorizing the data – may not do much to correct the errors. Moreover, an error for one group will have knock-on effects in our Other category. Specifically, in order to clear the market, outliers will force the residual Other group to also make an unrealistically large offsetting position change. This will affect the overall estimation of betas and lead to less informative inference. For these reasons, we *drop* these outlier observations for our analysis.

Nevertheless, as a robustness test, we repeat our analysis in Section 3 using (1) the raw data and (2) Winsorizing the outliers within each group at the 0.5 and 99.5 percentiles. These alternative specifications yield results that are qualitatively similar to our main results. See Appendix B.4 for these additional results.

[7] See Appendix B in Sammon and Shim (2023) for a detailed analysis of the mutual fund holdings data.

2.3 Empirical Methodology

Because passive funds have plausibly inelastic demand, we treat their position changes as a starting point to understand who clears the market. That is, our framework is built on the idea that passive funds demand liquidity by initiating the buying and selling. We develop a simple methodology to understand who takes the other side of passive trades.

It is important to note that our methodology is designed to identify long-term buyers and sellers of shares. While it is common for intermediaries, such as algorithmic trading firms and financial institutions, to be the most common counterparty on a day-by-day or trade-by-trade basis, their goal is often not to hold any portfolio in particular but to bridge the gap between final buyers and sellers. As a result, we will often not capture these types of investors. However, to the extent that these intermediaries take on strategic long-term bets and thus hold shares (or adjust their holdings of shares) over a quarter, they too will be counted as playing a role in market clearing.

Our methodology is built on estimating a series of univariate regressions, one for each of the nine, non-Index Fund groups, of the form

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}. \tag{5}$$

β_j represents the degree to which group j's demand responds to Index Fund demand. Throughout the paper, we use the language "Index Fund demand," "passive demand," "Index Fund changes," and "passive changes" interchangeably when referring to $q_{i,\text{IDX},t}$.

Because the market must clear in each stock each quarter, some other group or groups must be on the other side of passive changes. This can be mathematically represented as

$$\sum_j \beta_j = -1. \tag{6}$$

In words, Equation 6 says that all other groups in aggregate must collectively take the other side of passive position changes on a one-for-one basis for the marginal unit of demand due to market clearing. See Appendix A.3 for a derivation of this market clearing expression. In addition, the market must also clear for average passive demand. That is, the average Index Fund change across stocks and quarters must equal the sum of the average group change across stocks and quarters.

The estimated alphas and betas from Equation 5 tell us two things about market clearing. First, they tell us how the market clears *on average*. For example, if Active Funds have an average change of 0.011, this means that Active Funds collectively purchase 0.011% of the total ownership of the average stock each quarter.[8]

[8]The alphas by themselves tell us the fitted-value (i.e., predicted) for a stock-quarter with zero Index demand *given* the estimated sensitivity of each group's demand to Index Funds. For example, Active Funds have an alpha of around -0.05, which means in a quarter with zero passive demand, they are predicted to sell around 0.05% of each

The second thing we can learn from estimating Equation 5 is each group's *sensitivity* to Index Fund changes. The beta tells us how much each group's demand varies as a function of Index Fund demand. Specifically, for each additional percentage point of a stock's shares outstanding bought by Index Funds, group j tends to adjust their demand by β_j percentage points of shares outstanding. A group with positive beta means that, as Index Funds increase demand for a given stock-quarter, this group also increases its demand in that stock-quarter. This is also why the sum of the betas enters into the market clearing condition of Equation 6 – if one group demands more shares when Index Funds demand more shares, some other group must demand fewer shares.

3 Who Clears the Market?

In this section, we present our baseline linear estimates from the empirical specification described in Section 2.3. We then explore market clearing with fixed effects, for positive and negative passive demand shocks, and horizons of up to a year. We also briefly outline several robustness tests – full details can be found in Appendix B.

3.1 Baseline Linear Estimates

We estimate Equation 5 for each of the non-passive investor groups to account for how the market clears when Index Funds, in aggregate, add to or decrease their positions. Table 1 reports both the alpha and the beta for each group, as well as t-statistics, the number of observations, and the R^2.

In addition, we report the average position change for each group j, which we denote as $\overline{q}_j$. In the context of our regression framework, this can be interpreted as $\overline{q}_j = \alpha_j + \beta_j \cdot \overline{q}_{\text{IDX}}$, or the fitted value for q_j at the average level of passive demand $\overline{q}_{\text{IDX}}$. The average equal-weighted quarterly position change for Index Funds is 0.34pp (i.e., a position increase of 0.34% of a stock's total shares outstanding). Therefore, the sum of $\overline{q}_j$ for all j must be -0.34% of shares outstanding, because the shares that passive buys must come from a combination of the other groups.[9]

First, we highlight the average position change for each group $\overline{q}_j$. There are three groups that, for the typical firm, provide shares to Index Funds: Firms (-0.673 pp), Insiders (-0.074 pp), and Short Sellers (-0.053 pp). Note that these three groups collectively sell about 0.8 pp, much more than the 0.34 pp demanded by Index Funds on average. The reason for this is that all other groups, at least on an equal-weighted basis, also add to their positions on average, just like Index Funds.[10] This

stock.

[9]The sum of $\overline{q}_j$s may vary across tables because of subsample analysis or weighting differences. E.g., Table 12 reports value-weighted regressions and uses the corresponding value-weighted average change in passive ownership to compute $\overline{q}_j$ which differs from the equally-weighted average.

[10]It has been well documented that Active Funds in aggregate have seen redemptions over our sample period. This can be observed in our value-weighted analysis in Section 3.3.1, which captures this pattern in $\overline{q}_j$. In fact, given that

Table 1: Beta Estimates

Investor Group	β_j	$t(\beta_j)$	α_j	$t(\alpha_j)$	Obs.	R^2	$\overline{q}_j$
Active Funds	0.193	7.015	-0.052	-2.209	172,807	0.007	0.011
Other Funds	0.086	3.148	0.060	3.361	172,807	0.012	0.088
Pension Funds	0.022	7.423	-0.007	-1.243	172,807	0.004	0.000
Insurance	0.065	7.894	-0.029	-2.281	172,807	0.008	-0.008
Financial Institutions	-0.152	-2.265	0.123	1.445	172,807	0.001	0.073
Insiders	-0.084	-10.920	-0.033	-4.684	172,807	0.005	-0.060
Other	-0.250	-4.674	0.228	2.918	172,807	0.003	0.146
Short Sellers	-0.238	-6.433	0.037	0.802	172,807	0.015	-0.041
Firms	-0.642	-16.196	-0.327	-8.757	172,807	0.032	-0.537
Total	-1.000		0.000				-0.327

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t},$$

for each investor group j. $q_{i,j,t}$ is the quarterly holdings change (or changes in shares outstanding for Firms) in stock i for group j in year-quarter t in units of percent ownership of the company. $q_{i,\text{IDX},t}$ is the ownership change for Index Funds. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level. The last column reports the average quantity change for each group across all stocks and quarters ($\overline{q}_j$). See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology, and Section 3.1 for more details on the table.

first result shows that the typical share demanded by Index Funds comes from the supply side. Additionally, Firms and Short Sellers, on average, provide *all* of the shares typically demanded by not only Index Funds, but all other institutional investor groups.

Second, we highlight the sensitivities of each group to Index Fund demand. These estimates give a sense of the equilibrium responsiveness of each group: When Index Funds demand relatively more shares, who provides those *additional* shares? Here, the answer is again the supply side – when Index Funds demand an additional 1pp of a company's shares outstanding, Firms and Short Sellers collectively provide about 0.96 pp.[11] The combination of the market clearing averages and sensitivities suggests that Firms and Short Sellers on average provide all of the shares demanded by Index Funds.

Table 1 also shows that Active Funds, Pension Funds, and Insurance all have negative α_j and positive β_j. That is, the estimates suggest these groups are predicted to sell on average when Index Funds do not change their positions. These groups' positive betas imply that they tend to buy more of the stocks that Index Funds are buying relatively more intensely. One explanation for

the equal-weighted $\overline{q}_j$ for Active Funds is positive and the value-weighted $\overline{q}_j$ is negative, this implies that, as a group, Active Funds have tilted their portfolios toward small- and mid-cap stocks, while selling relatively large stocks to satisfy redemptions.

[11] One might be concerned that the negative relation between Index Fund demand and Short Seller demand is due to the fact that Index Funds often lend out their shares – creating a mechanical relationship between these two groups' demand. In Appendix C.4, we provide evidence that this channel does not explain the relationship between Index Fund and Short Seller demand.

this is that many Active Funds (and other demand-side institutions) are actually shadow-indexers, with a significant share of their capital invested in the index they are benchmarked to, and flows to Active and Passive funds of similar styles (e.g., value/growth or small-/large-cap) are correlated. Finally, in the average stock-quarter, these groups all also increase their positions ($\bar{q}_j > 0$).

Financial Institutions have a positive alpha but a negative beta, suggesting that they take the other side of marginal Index Fund demand on average. The residual Other group has a positive intercept but a much larger (in-magnitude) negative beta, suggesting that the residual group is more sensitive to large Index Fund demand shocks than Financial Institutions. We will show that the responsiveness of both groups can be better understood by examining nonlinearities in how their position changes vary as a function of Index Fund position changes in Section 3.1.2.

Before proceeding, we would like to highlight some patterns on statistical significance in Table 1 (we double-cluster standard errors at the stock and year-quarter level). The most statistically significant estimates are Firms' alpha and beta, with a t-statistic of -10.1 and -15.8, respectively. So not only are Firms' estimated coefficients the most negative, they are also the most reliably different from zero. Insiders, despite having a relatively small-in-magnitude alpha of -0.033 and a beta of -0.084, have the second-largest set of t-statistics of -4.7 and -10.9.

3.1.1 Fixed Effects

One concern with the results in Table 1 is that common time-series or cross-sectional shocks are driving our results, instead of Firms *responding* to Index Fund demand. To allay such concerns, we re-estimate Equation 5 including quarter-year, industry-by-quarter-year, and stock and quarter-year fixed effects. These specifications are designed to account for commonalities in Index Fund demand on a variety of dimensions. For example, the year-quarter fixed effects account for heterogeneity in Index Fund demand over time, while the industry-by-quarter-year fixed effects account for common demand shocks to particular sectors of the economy period-by-period.

Appendix B.1 provides the regression estimates for each fixed effects specification. Most of the beta estimates are largely unchanged – the supply side still accounts for more than 75% of the marginal shares needed to clear the market for passive position changes, with Firms providing more than half. This suggests that the overarching message of the baseline results also holds within a stock over time. This is in spite of the fact that the fixed effects soak up a significant amount of the variation in position changes. The R^2 of nearly every group's regression jumps significantly. In particular, the R^2 for Firms jumps from 0.034 in the baseline specification to 0.226 with fixed effects. Although not reported in Table 9, we find that most of the increase in R^2 comes from stock fixed effects, not year-quarter fixed effects.

3.1.2 Binscatter Plots

To identify possible nonlinearities in the relationship between each group's demand and Index Fund demand, we produce binscatter plots for each group's position change, measured in percent of shares outstanding purchased or sold, as a function of Index Fund position changes. We form 100 bins of equal size for each group, which means that each bin has more than 1,300 observations. These plots illustrate the expected position change of each group conditional on Index Fund changes.

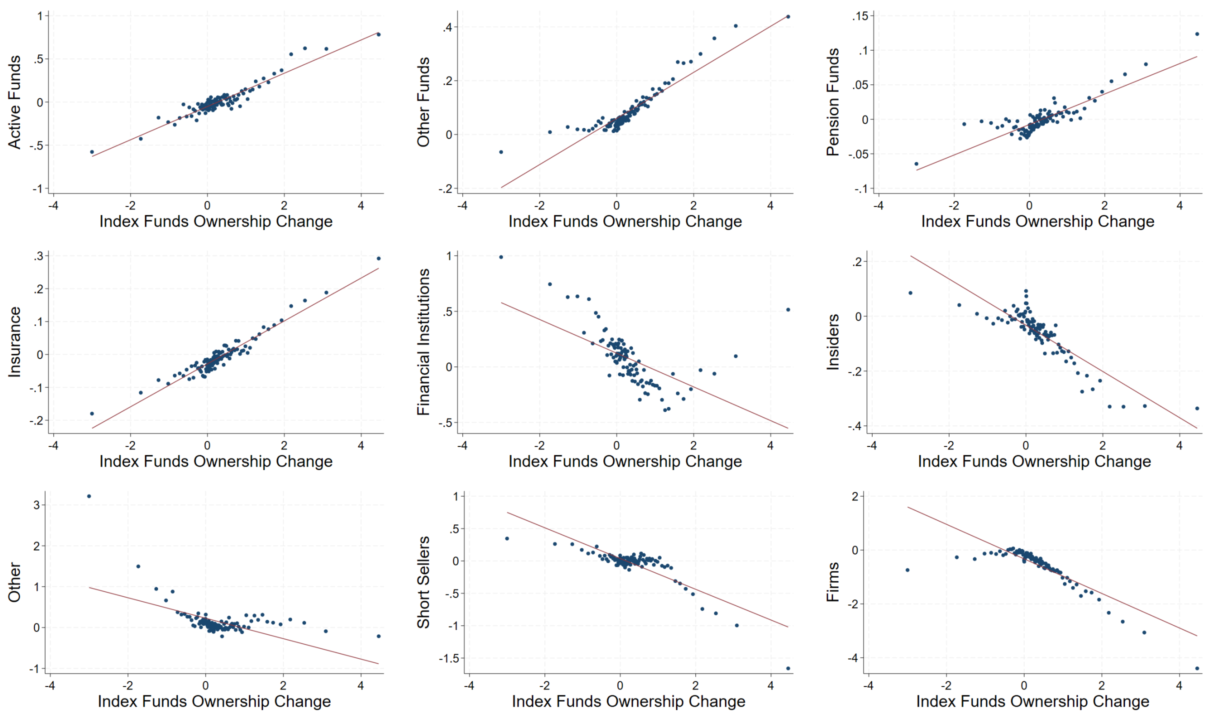
Our first takeaway is that the binscatter plots reinforce some patterns documented in Table 1. The conditional mean for Active Funds, Other Funds, Pension Funds, and Insurance is roughly linear in Index Fund demand. The plots also confirm the significant negative relationship between passive changes and the changes of Firms, Insiders, and Short Sellers. All three exhibit a similar pattern that is not clear from the beta estimates of Table 1: the negative relation is much stronger for positive passive changes than for negative. In fact, for Firms, it appears that, if anything, there is a weak positive relation between Firms' and Index Funds' position changes when passive changes are negative. In Section 3.1.3, we show that the estimate for Firm beta is around -1 for positive Index Fund demand and is 0.165 when Index Funds are net sellers.

Figure 4 also uncovers some patterns for Financial Institutions that are not obvious from Table 1 alone. Financial Institutions' position changes seem to have a clear negative relation with passive changes for all but the largest positive changes. For the largest passive changes, it appears that Financial Institutions mimic Index Funds. This suggests that Financial Institutions, which includes the trades of hedge funds, may indeed be on the other side of Index Funds for all but relatively large positive passive position changes.

Lastly, these figures provide a reasonable sanity check on the data: Can we reliably clear the market for Index Funds' position changes with our data-driven groups? Or, do we have to regularly rely on the residual Other group to clear the market? Figure 4 suggests that our results are not heavily dependent on our Other group clearing the market. For all but the extreme negative passive changes, the Other group has nearly a flat relation with passive share changes. That is, we can, on average, roughly capture market clearing amongst the groups in our data with the exception of the extreme negative share changes from Index Funds.

For these extreme observations, the groups in our data do not seem to take the other side of Index Funds and nearly all of our observed passive changes must be cleared by the residual group. In other words, the negative slope for the Other group in Table 1 is driven by stock-quarters where Index Funds are significant net sellers. Given the general trend toward passive buying over the past 20 years, in the cases of extreme passive selling there may be a concurrent event which explains why the groups in our sample do not clear the market. For example, suppose that due to a corporate event (e.g., redomiciling the firm for tax reasons) the stock became ineligible for many types of passive index funds and ETFs. In such cases, many institutions may also have mandates that

Figure 4: Ownership Changes: Binscatter by Group



Notes. Each panel presents a binscatter plot of demand by each investor group j – $q_{i,j,t}$ – on the y-axis against demand by Index Funds – $q_{i,\text{IDX},t}$. The unit of observation is security-year-quarter. The red line is the estimated slope in a univariate regression. Each binscatter plot uses 100 bins and plots the average of all observations within the bin. See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology, and Section 3.1.2 for more details on the figures.

prevent them from buying such stocks (Beber et al., 2021). This may be exactly the type of case where foreign institutional investors may take the other side, which would show up in our residual Other group.

3.1.3 Positive vs. Negative Demand Shocks

The binscatter plots in Section 3.1.2 show that Firms' and Short Sellers' demand has a negative relationship to Index Fund demand, but that it is driven entirely by firm-quarters where passive investors are net buyers of shares. To quantify this difference and to more formally understand who clears the market when Index Funds are net sellers, we re-estimate our baseline regressions but split the sample based on whether Index Funds' were net buyers or sellers of a stock. Table 2 presents the estimates for each subsample. Unsurprisingly, the number of observations in the positive change sample is much larger than the negative change sample, given the consistent growth of passive funds over this time period. There is still a sizeable sample – about a quarter of all observations – that saw Index Funds sell shares on net.

The beta estimates reveal several stark differences between these two subsamples. The right panel shows that when Index Funds buy shares, Firms on average issue shares on a one-for-one basis, with an estimated β of nearly -1. The left panel shows that when Index Funds sell shares, Firms do not clear the market by buying shares and instead sell alongside Index Funds, i.e., by issuing shares, although the magnitude is significantly smaller. Short Sellers exhibit a similar pattern to Firms in that they sell when Index Funds are buying but do not respond much to passive selling (unlike Firms, Short Sellers still have a negative beta).

So, who clears the market when Index Funds are net sellers? The left panel shows that the residual Other group contributes as much to clearing the market for Index Fund selling as Firms do for Index Fund buying. One explanation for this is that net selling by index funds may be the result of stocks leaving the investable universe (e.g., leaving the Russell 3000 or S&P 1500), thus making small institutional and retail investors more natural buyers since they may not be as concerned with tracking these major indices and they face fewer mandates against holding these stocks. Financial Institutions also have a negative beta estimate for passive selling, though it is much smaller in magnitude. These results suggest that the group that clears the market depends critically on whether a stock experiences a positive or negative demand shock from Index Funds.

3.2 Horizon Analysis

One way to interpret our baseline analysis is that it is a snapshot of who provides or holds additional shares as a result of inelastic demand shocks at a point in time. This raises questions about whether we are capturing longer-term intermediation instead of final buyers and sellers. For example, if

Table 2: Regression Estimates: Positive vs. Negative Passive Position Change

	Negative Passive Ownership Change						Positive Passive Ownership Change					
Investor Group	β_j	$t(\beta_j)$	α_j	Obs.	R^2	$\bar{q}_j$	β_j	$t(\beta_j)$	α_j	Obs.	R^2	$\bar{q}_j$
Active Funds	0.176	5.563	-0.045	46,131	0.003	-0.130	0.207	5.605	-0.066	125,870	0.006	0.065
Other Funds	0.027	2.438	0.040	46,131	0.001	0.027	0.109	2.971	0.041	125,870	0.014	0.128
Pension Funds	0.007	1.184	-0.014	46,131	0.000	-0.017	0.027	6.725	-0.011	125,870	0.005	0.007
Insurance	0.046	5.169	-0.035	46,131	0.002	-0.057	0.073	6.545	-0.034	125,870	0.007	0.022
Financial Institutions	-0.333	-3.949	0.134	46,131	0.004	0.295	-0.033	-0.366	0.011	125,870	0.000	0.030
Insiders	-0.024	-2.668	-0.007	46,131	0.000	0.005	-0.104	-8.923	-0.019	125,870	0.005	-0.109
Other	-0.950	-9.390	-0.056	46,131	0.026	0.402	-0.006	-0.080	0.049	125,870	0.000	0.149
Short Sellers	-0.136	-2.874	0.008	46,131	0.003	0.074	-0.320	-7.028	0.118	125,870	0.019	-0.115
Firms	0.185	6.132	-0.025	46,131	0.002	-0.114	-0.953	-16.097	-0.089	125,870	0.047	-0.864
Total	-1.002		-0.000			0.483	-1.001		0.001			-0.685

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. The sample is split based on whether Index Funds were net buyers in a given stock in a given quarter (positive passive position change) or whether they were net sellers in a given stock in a given quarter (negative passive position change). The unit of observation is security-year-quarter. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

Index Funds buy shares which are provided by an intermediary (e.g., a hedge fund) that typically is a net seller of those shares for about a quarter but then buys them back, our analysis will miss the group that is the final provider of shares to Index Funds in the long run.

To better understand how market clearing evolves over longer frequencies, we re-estimate our tests using position changes for each of our groups over not just 1 quarter, but cumulatively over 2, 3, and 4 quarters. This results in regressions with data that is partially overlapping. While the unit of observation is still at the stock and year-quarter level, demand for stock i in quarter t will capture not just position changes in quarter t but the cumulative change from t to up to 4 quarters ahead. Because we have overlapping observations, we adjust standard errors by clustering at the stock- and year-quarter-level as well as for autocorrelation *up to* 6 quarters, i.e., we follow the standard practice of including lags equal to 1.5 times the number of overlapping observations. We also re-estimate the 1-quarter horizon from the baseline analysis because we adjust the sample to require at least 4 consecutive quarters of non-missing data for each stock. Thus, the sample is identical across the four different horizons we test, the only difference is how many quarters we accumulate position changes over.

Table 3 provides the beta estimates for the 1, 2, 3, and 4 quarter horizons. The most notable change is that Firms clear the market for nearly all shares demanded by not only Index Funds but all other groups that tend to mimic Index Funds. Firms' beta estimate increases in magnitude over each horizon, from -0.59 at 1 quarter to -0.86 and -1.08 at 2 and 3 quarter horizons, and finally to -1.24 at the year-over-year horizon. The coefficient is larger in magnitude than -1, which indicates that Firms are providing shares at a greater than one-for-one rate. The reason is that all large demand-side institutions increase the degree to which they mimic Index Fund demand over longer

Table 3: Horizon Analysis

	1 Quarter		2 Quarters		3 Quarters		4 Quarters		
Investor Group	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	Obs.
Active Funds	0.165	4.784	0.226	5.598	0.253	6.563	0.275	7.872	140,583
Other Funds	0.084	2.425	0.113	3.244	0.130	3.904	0.143	4.452	140,583
Pension Funds	0.021	6.663	0.030	6.790	0.032	6.971	0.036	7.887	140,583
Insurance	0.066	6.798	0.088	9.901	0.091	12.338	0.095	12.861	140,583
Financial Institutions	-0.210	-2.639	0.103	0.925	0.245	2.285	0.355	3.423	140,583
Insiders	-0.071	-8.544	-0.105	-7.364	-0.126	-6.935	-0.143	-6.921	140,583
Other	-0.243	-4.200	-0.360	-2.717	-0.305	-2.086	-0.262	-1.931	140,583
Short Sellers	-0.219	-4.970	-0.230	-6.015	-0.245	-8.188	-0.258	-10.561	140,583
Firms	-0.594	-17.727	-0.863	-15.142	-1.075	-14.558	-1.239	-13.129	140,583
Total	-1.001		-0.998		-1.000		-0.998		

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t\to t+\ell} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t\to t+\ell} + \varepsilon_{i,j,t},$$

for each investor group j. $q_{i,j,t\to t+\ell}$ is the quarterly holdings change in stock i for group j from the beginning of year-quarter t to the end of $t+\ell$, where ℓ ranges from 0 to 3, in units of percent ownership of the company. $q_{i,\text{IDX},t\to t+\ell}$ is the cumulative ownership change for Index Funds. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level and we control for autocorrelation up to 6 lags due to partially overlapping data. See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology, and Section 3.2 for more details on the table.

horizons. Active Funds' beta estimate nearly doubles, and Financial Institutions' beta increases in magnitude and *completely flip sign*. In other words, Financial Institutions help clear the market for passive demand at the quarter horizon, but add to Index Fund demand at anything longer than a quarter horizon. In fact, in the year-over-year analysis, Financial Institutions demand is the largest in magnitude of any of our 9 groups with the exception of Firms. Short Sellers and Other, the other two groups that help clear the market for passive demand, have a steady contribution over the four different horizons.

Appendix B.2 repeats the horizon analysis, but separately for positive and negative Index Fund demand shocks. We find a similar pattern to the signed analysis in Section 3.1.3. In fact, in the long run (i.e., the year-over-year horizon), we find that Firms are essentially the sole providers of shares for positive Index Fund demand shocks and our residual Other group is the sole purchaser of shares for negative shocks. In fact, every large demand-side institution trades on average in the same direction as Index Funds over the horizon of a year, and the effect is most pronounced for negative passive demand shocks. This is further evidence that when Index Funds are net sellers of a stock over the course of a year, the stock is likely leaving the investable universe from the perspective of large institutions and they sell shares en masse.

3.3 Robustness Tests

We perform several robustness tests for the main equal-weighted regression results. We briefly describe each test below – and provide the full details and tables in the appendix.

3.3.1 Value-Weighted Regressions

To capture market clearing for the marginal *dollar* of passive demand, we re-estimate the regressions from Section 3.1 on a value-weighted basis. With value weights, we find that Firms are still the group that contributes the most to clearing the market for the marginal unit bought or sold by Index Funds. On the other hand, relative to our baseline equal-weighted specification, Active Funds and Financial Institutions play a larger role in clearing the market for average Index Fund demand. We describe the value-weighted results in detail in Appendix B.3.

These findings help establish that our baseline results on marginal market clearing are not dominated by small- and mid-cap companies and are robust to the increased prevalence of buybacks, especially for very large companies. It is important to remember that, while buybacks have drawn attention from the media, 80% of company-quarters have net issuance, and the issuance as a percentage of the overall size of the company is larger on average than buybacks. We provide these supporting facts and greater detail in Appendix D.1.

3.3.2 Sample Selection and Treatment of Outliers

In Appendix B.4, we provide additional estimates for different sample periods (2009-2021 and 2015-2021) and different treatment of outliers (raw data and Winsorization). Most of the patterns in our baseline sample are also found in these alternative samples. Notably, Firms' beta estimates are even more negative in recent years than over the whole sample. Moreover, Active Funds consistently respond in the same direction as Index Funds, with beta estimates ranging from 0.180 to 0.506.

The most notable differences in these alternative samples are for the Other group when adding back extreme observations. The beta estimates range from -0.642 (Winsorized) to -1.325 (raw), a large difference from our baseline estimate of -0.250. This suggests that our residual Other group does more work in clearing the market when including more extreme observations (i.e., when the market does not clear among the investor groups we can directly observe in the data). This provides some suggestive evidence that these extreme observations may be data errors, supporting our decision to remove them from our main sample.

3.3.3 Data Errors

As described in Section 2 and documented in detail in Sammon and Shim (2023), the S12 data are littered with many types of errors, some of which involve staleness in reported holdings. In the Appendix, we discuss two sets of tests designed to address such data errors.

The first type of issue is due to general data errors where a group appears to increase or decrease its ownership of a stock but does not in reality. Such an error will force the Other category to absorb this seemingly unmet demand. In Appendix B.5, we rerun a version of our baseline regressions, limiting the sample to only stock-quarters where the Other group has an ownership change of less than 0.5 pp in magnitude, i.e., stock-quarter observations where we are confident these types of data errors are less likely to alter the beta estimates. Table 15 shows that the results for this subsample are consistent with the baseline results – Firms and Short Sellers collectively account for a significant fraction of the marginal shares demanded by passive.

The second and more specific issue that could contaminate our results is stale data. Suppose, for example, that Index Funds buy a stock in period t and Active Funds sell to them, but Active Funds' sales are erroneously not recorded in the data and stale holdings from the previous quarter are reported instead. Then, the passive buying in quarter t will appear to be cleared by the Other group selling in period t. Furthermore, if Active Funds' sales, that actually occurred in t, are recorded in quarter $t+1$, the Other group will need to buy to clear the market.

To quantify the effects of possibly stale data on our baseline regression results, in Appendix B.5 we test the degree to which passive changes in quarter t are related to other groups' position changes in the same stock but in quarter $t+1$. Given the example above, in the presence of stale data we expect to observe a negative relation between the residual Other group's position change in t and Index Fund demand at t, but a positive relation between the residual group's position change at $t+1$ and Index Fund demand at t. Table 16 shows that this is indeed the case. The Other group's $t+1$ estimate is 0.097, suggesting that only a small fraction of the residual group's tendency to take the other side of Index Fund demand in t is indeed reversed in $t+1$. As a benchmark, if the Other group's entire beta estimate in t were to offset stale data, the beta in t and $t+1$ would be equal in magnitude but of the opposite sign.

3.3.4 Over Time

We estimate our set of regressions each quarter and report the beta estimates over time. That is, these betas are only identified using *cross-sectional* variation in Index Fund demand period-by-period. We plot an 8-quarter moving average of our beta estimates in Figure 12. We find that Firms' betas have been getting more negative and closer to -1 over time. See Appendix B.7 for more details.

3.3.5 Thematic and Broad-Based Funds

So far, we have treated Index Funds as one group. However, as discussed in the introduction, one may be concerned that our results are driven by common fundamental shocks which coordinate Index Fund and Firm demand. In this case, one might believe that there are significant differences in our findings for broad-based index funds (e.g., S&P 500 or Russell 1000 funds) and style funds (e.g., industry or factor funds). The logic is that demand for style funds is more likely to be coordinated by common fundamental shocks – because their positions are more concentrated – and therefore these types of funds may be entirely driving our main results.

To see the contribution of different types of index funds, we separate demand in our Index Fund group into demand from broad-based funds and style funds. We draw two main conclusions from this analysis. First, Firms are still the most responsive group to Index Fund demand, regardless of whether we focus on broad-based or style Index Funds. Second, and perhaps more surprisingly, Firms are much more responsive to broad-based than style Index Funds' demand. We believe this is in part because, for broad-based Index Fund buying, there is more overall inelastic demand that needs to be accommodated, as style funds tend to partially mimic the demand of broad-based funds. We provide details in Appendix B.8.

3.3.6 Index Switching Stocks

We analyze market clearing with respect to shocks to index inclusion. We provide two sets of results, which we describe in detail in Appendix B.9: (1) Estimates for stocks that did or did not switch from one major index to another (e.g., switches within the Russell or S&P family of indices), and (2) more granular estimates based on switching from a specific major index to another (e.g., migrations from the Russell 1000 to 2000) or direct additions or deletions (e.g., stocks moving into or out of the S&P 1500 universe).

We find that the results for index stayers largely tell a similar story to our baseline findings: Firms account for most of the other side of passive demand, with Short Sellers and Insiders also consistently contributing to clearing the market for Index Fund buying/selling. Market clearing, however, is quite different for index switchers. Most notably, Firms play a much larger *average* role: $\overline{q}_j$ for Firms is -1.082pp, nearly all of the 1.102pp average Index Fund demand for index switchers. However, Firms are much less *responsive*, with a beta estimate of -0.201 (as opposed to -0.763 for stayers). This analysis is broadly consistent with the results in Tamburelli (2024), who shows that firms accommodate inelastic demand from index trackers around S&P 500 index inclusion events. One main difference from our approach is that Tamburelli (2024) studies S&P 500 additions, with the inclusions serving as an instrument for passive demand in a high-frequency setting. Our analysis is instead focused on the quarterly horizon, and is meant to highlight differences in market clearing for the subset of all additions/deletions/switchers from major index families. These differences in approach and objective may account for the quantitative differences in our findings.

4 Identification and Instrument

So far, our results establish a strong negative correlation between Index Fund demand and Firm demand. In this section, we aim to understand the mechanism behind this relationship, specifically *why* Firms appear to respond to Index Fund demand by issuing shares. We propose three likely channels that could generate the observed relationship in the data.

Our preferred mechanism, and the one that is most supported by the evidence, is that prices coordinate market clearing. Specifically, when Index Fund demand shocks occur, prices increase due to their inelastic nature. In response, Firms issue shares to capitalize on high prices (Loughran and Ritter, 1995; Graham and Harvey, 2001; Baker and Wurgler, 2002; Dong et al., 2012; Ma, 2019).

Another possible mechanism is that common fundamental shocks coordinate Firm and Index Fund demand. For example, the commercialization of AI (Eisfeldt et al., 2023b) might drive technology firms to invest in GPUs and hire new employees, which they fund by issuing equity and attract human capital by granting stock to employees. Simultaneously, investors excited about the potential of commercialized AI may increase their demand for ETFs that hold stocks poised to benefit from AI technology. In this case, an omitted variable – namely, the common technology shock – coordinates Index Fund and Firm demand.

A final possible mechanism is reverse causality, due to the mechanical way Index Funds trade in response to Firm issuance and buyback activity. For instance, when a Firm issues shares, the number of "index-eligible shares" increases, leading to mechanical buying by Index Funds.

To isolate prices as the coordinating device for Index Fund and Firm demand, we propose an instrumental variables (IV) specification. Our IV results suggest that the effect of Index Fund demand on prices, rather than omitted common fundamental shocks or reverse causality, is the primary driver of our OLS regression results in Section 3.1. We also provide direct evidence for the price channel, demonstrating in Section 5.1 that the relative valuation of a stock – as measured by excess earnings yield and Tobin's Q – is a strong predictor of how Firms respond to Index Fund demand. We conclude this section by discussing a series of additional tests designed to rule out the mechanical/reverse causality channel as the main driver of our results.

Before presenting the IV findings, we would like to emphasize that these results will not alter our main conclusions in Section 3 because market clearing is an identity. In other words, our IV results *cannot* change the cross-sectional and time-series regularity of Firms clearing the market for Index Fund demand (and passive buying in particular). Instead, they can help inform *why* Firms are the most responsive group to Index Fund demand.

4.1 Instrumental Variables Approach

As outlined above, our preferred explanation for the relationship between Index Fund and Firm demand is that prices coordinate market clearing. One alternative explanation is the omitted variables problem, i.e., that firm-level or common fundamental shocks coordinate Index Fund and Firm demand. Therefore, we aim to identify shocks to Index Fund demand that are uncorrelated with stock-level, industry-level, and factor-level fundamentals. Further, to address reverse causality, we leverage the part of Index Fund demand driven by *flows*, which is distinct from the mechanical way Index Funds must adjust their holdings in response to Firm activity.

To build intuition for the logic behind our instrument, consider the following example. Suppose we are interested in constructing an instrument for Index Fund demand in the stock of a manufacturing company. Further, suppose that there is only one index fund and this index fund holds the manufacturing stock of interest, which we refer to as the "focal stock". In addition, at the time of constructing the instrument, the focal stock is a large-cap, high book-to-market (i.e., value) with low past returns (i.e., momentum loser). The idea of our instrument is to exploit variation in the returns of all stocks that are not large-cap, value, past return losers and are not in the broad manufacturing sector. In our singular index fund, this might leave only, e.g., a small-cap tech stock and bank stock. Suppose then that the tech and bank stocks perform well in a given quarter. Then, this index fund will likely have inflows due to return-chasing activity from investors. Importantly, due to the way index funds scale up and down holdings in response to flows (Sammon and Shim, 2023), the index fund will buy *all* the stocks in the index, not just the stocks that triggered the inflow. In other words, the index fund will buy the manufacturing stock because the small-cap, growth, low-past-return tech and bank stocks did well.

Empirically, to construct our instrument, we utilize the flow-performance relationship in passive funds, i.e., the fact that passive funds experience inflows after good fund returns and outflows after poor returns.[12] More specifically, we aim to identify stocks that experienced buying or selling because the index funds that hold them experienced flows based on the performance of "co-holdings," or sufficiently unrelated stocks that are held in the same fund. To do this, we need to ensure that these flows are not driven by common fundamental shocks affecting both the stock in question and its co-holdings. To this end, we construct a *leave-out* return which excludes stocks that are likely similar to the focal stock and compute returns for the remaining, unrelated stocks.

To construct these leave-out co-holdings returns, for each focal stock i at the end of each quarter t, we identify all funds k in the set of all funds K that hold the stock. Then for each fund $k \in K$,

[12] See Appendix C.3 for our quantitative estimates of the strength of the flow-performance relationship for passive funds.

at $t-1$ we drop the stock itself and stocks in the same Daniel et al. (1997) $5 \times 5 \times 5$ portfolio formed on size, book-to-market, and past returns (hereafter DGTW portfolio). We also exclude any stock in the same Fama-French 10 industry. We believe that excluding all stocks in the broader FF 10 industry group – as opposed to, e.g., the more granular Fama-French 49 industry group – is a conservative choice to exclude as many common fundamental shocks as possible. The goal of this filtering strategy is to identify co-holdings that are not similar on the dimension of size, book-to-market, past return, and industry.

Within each fund k, we re-weight all the stocks that survive these filters in proportion to how much the fund held of each stock at $t-1$. Finally, we compute the buy-and-hold returns to this re-weighted portfolio from the end of quarter $t-1$ to the end of quarter t, which we denote as $r_{i,k,t}^{coholdings}$, and refer to this as the stock-fund-quarter co-holdings return in quarter t. We also calculate the co-holdings return for fund k the previous quarter – $r_{i,k,t-1}^{coholdings}$ – following the same methodology, i.e., excluding stocks that were in the same industry and DGTW portfolio as stock i in quarter $t-2$, and computing the hypothetical buy-and-hold returns from the end of quarter $t-2$ to the end of quarter $t-1$. We compute $r_{i,k,t}^{coholdings}$ and $r_{i,k,t-1}^{coholdings}$ even if stock i was not held by fund k at the end of quarter $t-2$ or $t-1$, as these past co-holdings returns could still drive flows into stock i when it was held in quarter t.[13]

After computing $r_{i,k,t}^{coholdings}$ and $r_{i,k,t-1}^{coholdings}$ for each individual fund k that holds stock i, we aggregate these returns to the stock-quarter level. We do this by taking a weighted average of the co-holdings returns for all index funds $k \in K$ holding the stock at the end of quarter t, where the weights are proportional to stock i's weight in each fund's portfolio.[14] Specifically, we compute:

$$\overline{r}_{i,t}^{coholdings} = \sum_{k \in K} w_{i,k,t} \cdot r_{i,k,t}^{coholdings},$$

where $w_{i,k,t}$ is the weight of stock i in fund k at time t, which have been renormalized to sum to one within each stock-quarter. We use the same weighting scheme to compute $\overline{r}_{i,t-1}^{coholdings}$. To reduce

[13] Our IV specification has fewer observations than our OLS regression, as some stocks do not have any co-holdings that survive all filters proposed above, and thus have missing values for $\overline{r}_{i,t}^{coholdings}$ and $\overline{r}_{i,t-1}^{coholdings}$.

[14] One natural alternative is to weight by the percent of stock i's market capitalization held by each fund, which should predict the size of the demand shock – as a fraction of stock i's market capitalization – given percentage fund flows (Sammon and Shim, 2023). We prefer weighting by portfolio weights for several reasons. From a practical perspective, we find the strongest first-stage regression when weighting by the stock's weight in each fund (i.e., it makes our weighted average co-holdings returns a relatively better predictor of Index Fund demand). This is likely due to the stronger flow-performance relationship for funds with more concentrated holdings, as shown in Appendix C.3 – and the larger expected price impact of such funds receiving flows and re-investing in their relatively smaller holdings set (van der Beck et al., 2024). More broadly, our goal is to identify demand shocks uncorrelated with own-firm fundamentals and similar firms' fundamentals. Funds with more concentrated holdings – and thus larger individual stock weights – likely contain more idiosyncratic shocks from a few stocks unrelated to the focal stock i's returns. A large diversified fund like IWM (Russell 2000) or IWB (Russell 1000), is unlikely to have any small individual group of co-holdings driving the fund's returns without a significant systematic component. As additional robustness, we explicitly estimate expected flows given the flow-performance relationship at the fund-level to match the units between expected and realized Index Fund demand in Appendix C.3.

the influence of outliers, we Winsorize $\overline{r}_{i,t}^{coholdings}$ and $\overline{r}_{i,t-1}^{coholdings}$ at the 0.5% and 99.5% level.[15] We then use these quantities in our first-stage regression to predict Index Fund demand in stock i in quarter t:

$$q_{i,IDX,t} = \gamma_t \cdot \overline{r}_{i,t}^{coholdings} + \gamma_{t-1} \cdot \overline{r}_{i,t-1}^{coholdings} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{Fixed Effects} + e_{i,t}. \quad (7)$$

Given the goal of our IV strategy is to identify passive demand unrelated to own-firm fundamentals, we include the firm's own standardized unexpected earnings (SUE) in quarters t and $t-1$ as controls. To account for common technology shocks, we include Fama-French 10 industry-by-year-quarter fixed effects. The inclusion of these fixed effects implies that our key source of identifying variation is differences in the co-holdings returns of stocks in the same industry, at the same point in time, which were included in different sets of index funds and ETFs, and therefore had differences in their average co-holdings returns. We include two lags of co-holdings returns and SUE because the flow-performance relationship is persistent. As an additional check against a possible look-ahead bias, we show our IV results are robust to excluding the contemporaneous co-holdings returns $\overline{r}_{i,t}^{coholdings}$ in Appendix C.2.

Intuitively, our instrument consisting of co-holdings returns is meant to capture the performance of relatively unrelated stocks held in the same funds. A high value of $\overline{r}_{i,t}^{coholdings}$ and $\overline{r}_{i,t-1}^{coholdings}$ indicates that a stock's co-holdings performed well; similarly, a low value indicates the co-holdings performed poorly. This variation in co-holdings returns will predict Index Fund buying and selling in the first stage if investors in Index Funds chase returns, even if the fund-level returns are driven by fundamentally unrelated stocks. In addition, the inclusion of SUE as a control and industry-by-year-quarter fixed effects helps remove firm-specific information and common components of returns that may remain in the instrument.

Our second-stage regression is:

$$q_{i,j,t} = \beta \cdot \hat{q}_{i,IDX,t} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{Fixed Effects} + \varepsilon_{i,j,t}, \quad (8)$$

Equation 8 contains the same controls and fixed effects as the first-stage regression in Equation 7. With these controls and fixed effects, the key source of variation we are exploiting is heterogeneity within a Fama-French 10 industry at a given time between stocks whose unrelated co-holdings performed relatively better versus those that performed relatively worse.

A natural question is: If we are interested in measuring the effect of passive demand on prices, why

[15] This differs from our treatment of outliers in Section 2.2.3, were we *trimmed* our $q_{i,j,t}$s at the 0.5% and 99.5% levels – removing 7.5% of all observations – instead of Winsorizing. We Winsorize $\overline{r}_{i,t}^{coholdings}$ and $\overline{r}_{i,t-1}^{coholdings}$ because we do not want to drop additional data when constructing the IV. This is in contrast to our data in the market clearing exercise since extreme outliers create the need to clear the market by some other group, i.e., the errors may propagate to the Other group to ensure that the market clears. If instead we use the raw values for $\overline{r}_{i,t}^{coholdings}$ and $\overline{r}_{i,t-1}^{coholdings}$ in our IV specification, the results are even stronger, both in terms of the estimated magnitudes and statistical significance.

do we not include $r_{i,t}$ on the right-hand side of Equation 8? We believe $r_{i,t}$ is a "bad control" in the sense that our IV approach focuses on inelastic demand shocks, which affect prices and coordinate market clearing. Controlling for prices would be controlling for the mechanism we think facilitates market clearing in the first place.

Table 4 presents the results. In this subsection, we focus on the case where Firm demand, $q_{i,Firm,t}$, is on the left-hand side of Equation 8. The first column shows a strong first stage with an F-statistic over 20. Further, each instrument predicts passive demand with the expected sign, i.e., higher co-holdings returns predict more passive inflows. The second column presents the IV results, where the magnitude is slightly larger and consistent with the OLS results, reported in column 4. The reduced form regression in column 3 shows the regression of $q_{i,Firm,t}$ directly on the instruments themselves. Again, each instrument predicts $q_{i,Firm,t}$ with the expected sign and is (marginally) significant, addressing concerns about weak instruments potentially driving our results (Chernozhukov and Hansen, 2008).[16]

We interpret the results in Table 4 as supporting the conclusion that prices, rather than omitted common shocks or reverse causality, coordinate Firms clearing the market for inelastic Index Fund demand. While previous research has established that Firms respond to prices Loughran and Ritter (1995); Graham and Harvey (2001); Baker and Wurgler (2002); Dong et al. (2012); Ma (2019), none of these results on their own imply that Firms would be the *most responsive* group, especially in a causal setting.

A natural next question is that if prices are the coordinating driver of Firm and Index Fund demand, how does that change the interpretation of our OLS results? Recall that the IV is designed to isolate non-fundamental Index Fund demand shocks, i.e, plausibly exogenous inelastic demand. Given the similarity in the magnitudes of the estimated effect in the IV and OLS regressions, this suggests that Firms respond just as much to non-fundamental Index Fund demand shocks as to the endogenous demand shocks in the OLS regression. This suggests that the Index Fund demand *itself* is what's important for how Firms respond. This is outside of a traditional Q-theoretic framework where firms only raise capital when they have attractive investment opportunities.

4.2 Alternative Instrument

Implicitly, our first stage regression in Equation 7 assumes that returns of co-holdings predict flows and does so equally across funds. Empirically, however, there is significant heterogeneity in the flow-performance relationship for index funds. Even with the assumption of an equal flow-performance relationship across funds, the strength of our first-stage regression suggests that there is a flow-performance relationship *on average*. In Appendix C.3, we refine our baseline IV setup to

[16] In Appendix C.1, we present the IV results for all of our individual investor groups. Table 21 confirms that our main finding – i.e., that Firms are the most responsive to Index Fund demand – holds true in our IV setting.

Table 4: Instrumental Variables Specification

	First Stage	IV	RF	OLS
$\overline{r}_{i,t-1}^{coholdings}$	1.045***		-1.433*	
	(0.253)		(0.842)	
$\overline{r}_{i,t}^{coholdings}$	1.567***		-1.004	
	(0.330)		(0.758)	
$SUE_{i,t}$	0.00463***	0.0105**	0.006	0.00946**
	(0.001)	(0.005)	(0.005)	(0.005)
$SUE_{i,t-1}$	0.00373***	0.0145**	0.0112**	0.0136**
	(0.001)	(0.006)	(0.005)	(0.005)
$q_{i,IDX,t}$		-0.864**		-0.627***
		(0.389)		(0.037)
Observations	130,794	130,794	130,794	130,794
R-squared	0.1	0.026	0.033	0.062
F-statistic	23.26			
Fixed Effects	FF 10 Industries × Year-Quarter			

Notes. The table provides estimates from the first and second stages of our IV regression, as well as the associated reduced form and OLS regressions. The first and second stage regressions are:

$$q_{i,IDX,t} = \gamma_t \cdot \overline{r}_{i,t}^{coholdings} + \gamma_{t-1} \cdot \overline{r}_{i,t-1}^{coholdings} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + e_{i,t}$$
$$q_{i,Firm,t} = \beta \cdot \hat{q}_{i,IDX,t} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + \varepsilon_{i,Firm,t},$$

where $\overline{r}_{i,t}^{coholdings}$ and $\overline{r}_{i,t-1}^{coholdings}$ are the weighted average leave-out co-holdings returns across all index funds $k \in K$ that held stock i at the end of quarter t and $t-1$. $SUE_{i,t}$ is the standardized unexpected earnings (SUE) of stock i in quarter t. FE are a set of Fama-French 10 industry-by-year-quarter fixed effects. Standard errors are double clustered at the stock and year-quarter level. The first column reports the first stage regression, the second column reports the IV specification, and the third column reports the reduced-form regression. The final column reports the OLS results, but restricting to the sample with non-missing values for the instruments and a matched set of controls and fixed effects to the first three columns. See Section 4.1 for more details on the instrument and the table.

account for this heterogeneity, estimate the flow-performance sensitivity at the fund level, then use each fund's sensitivity along with the previously calculated stock-quarter-level leave-out co-holdings returns to compute expected flows into each fund each quarter.[17] We then use these expected flows to calculate expected demand shocks at the stock-fund-quarter level, building on the fact that index funds proportionally scale all holdings up and down in response to flows. Finally, we directly aggregate this quantity (which is in share terms) across all funds that hold each stock. We call this alternative measure of expected Index Fund buying $\tilde{q}_{i,IDX,t}$, and is akin to the expected Index Fund demand that emerges from a first-stage regression and is used in a second-stage regression. Although this approach potentially introduces noise by using the *estimated* flow-performance relationships, it can help reconcile differences in magnitudes between the IV and OLS regressions. Unlike the returns in the reduced form regression in Table 4, the estimated demand shock will be in the same units as $q_{i,IDX,t}$.

As an example of this instrument, consider two index funds that all hold some stock i. This alternative instrument will allow for each fund to have a different flow-performance relationship, with one that has more inflows in response to high returns than the other (i.e., one has more flow-performance sensitivity). For stock i, we use the co-holdings return for each fund, then use that return and that fund's flow-performance sensitivity to predict flows for that fund specifically. Because index funds typically scale positions up and down in response to flows (Sammon and Shim, 2023), we proportionally allocate that predicted flow to stock i. So, if stock i had a high co-holdings return but was in the fund with low flow-performance sensitivity, we may predict little buying – the co-holdings return does not predict much demand. Alternatively, if stock i was in the high-sensitivity fund and a moderately high co-holdings return, we may still predict a large amount of buying – despite the fund having a moderate co-holdings return, as investors in this fund are much more sensitive and these returns lead to bigger flows and significant buying in stock i by this fund. For our measure, we then add up the predicted buying across both funds to have a measure of predicted demand. This amounts to the sum of how much each fund would buy of stock i based on each fund's (1) co-holdings returns and (2) sensitivity in flow-performance.

We report the results in Appendix Table 23. The regression of $q_{i,Firm,t}$ on $\tilde{q}_{i,IDX,t}$, i.e., our alternative measure of expected index fund buying yields a coefficient of -0.88. This is reassuring on two levels. First, it again confirms the *causal* nature of the relationship between Index Fund demand and Firm issuance. In addition, it directly aggregates quantities to "build" a first stage instead of using returns as an instrument in the first stage. This helps address the concern that aggregating co-holdings returns, even from unrelated stocks, can recover common factors in returns and thus essentially just capture returns in the focal stock itself.

As an additional robustness check against a possible look-ahead bias and the endogeneity of time t

[17]While we compute expected flows at the fund-quarter level, we would like to highlight that this quantity varies across stocks in the same fund at a given point in time. This is because we use the stock-fund-quarter-level leave-out co-holdings returns to compute expected flows, and these co-holdings returns could be different for every stock.

returns, we construct a version of $\tilde{q}_{i,IDX,t}$ that uses only the lagged flow-performance relationship and lagged co-holdings returns. These findings, also reported in Appendix Table 23, confirm that our main results still hold.

5 Why and How Do Firms Provide Shares?

In this section, we further explore mechanisms for why and how Firms provide shares to Index Funds. First, we more explicitly study the role of prices in Firms' willingness to clear the market in Section 5.1. Second, we provide more details on the mechanical relationship between Firm activity and Index Fund demand, how it works, and why it cannot be the main driver of our results in Section 5.2. Third, we explore how exactly Firms issue shares and/or reduce the size of buybacks to accommodate greater passive demand in Section 5.3. Lastly, we provide some evidence in Section 5.4 that much of the issuance that does not come from SEOs comes instead from stock used as compensation to employees.

5.1 Firms as the Marginal Arbitrageurs in their Own Shares

In Section 4.1, we constructed an IV designed to rule out the effect of common fundamental shocks and therefore "rule-in" the role of prices – concluding that prices appear to be the driving force that coordinates market clearing in our setting. To more explicitly test this mechanism, we study how prices affect Firms' responsiveness to Index Fund demand. Past work has shown that firms issue equity when they think their stock is overvalued (Loughran and Ritter, 1995; Graham and Harvey, 2001; Baker and Wurgler, 2002). Our findings in Sections 3 and 4 point to the possibility that not only do Firms sell when their shares are overpriced, but Firms are also the *marginal* seller of shares when prices are high.

Based on the idea that Firms are the marginal provider of shares for Index Fund demand and prices are the market-clearing coordination device, we predict that Firms would be more willing to accommodate passive demand when their shares look expensive relative to when they look cheap. Further, Firms' likely have private signals about their true value, which may lead them to issue equity in response to seemingly high prices exactly when they are overvalued, rather than because the firm has significant growth opportunities (Daniel and Titman, 2006). This is important in our setting, as Firms may be in the best position to assess if passive demand has pushed up prices for non-fundamental reasons. Finally, because Firms can only "trade" in their own shares, one might expect that Firms' tendency to clear the market for passive demand when shares are overvalued is the most sensitive of all investors groups.

To this end, we are interested in quantifying how the responsiveness of each group is affected by how expensive a given stock is. As a simple measure to capture this, we use excess earnings yield ($EXEY$), defined as:

$$EXEY_{i,t} = \frac{TTM\ EPS_{i,t}}{P_{i,t}} - r_{rf,t},$$

where $TTM\ EPS_{i,t}$ is the trailing 12 months earnings per share (EPS), $P_{i,t}$ is the price at the end of the quarter, and $r_{rf,t}$ is the 10-year Treasury rate. To strip out the effect of extraordinary items, we use "street" earnings from IBES as our measure of EPS (Hillenbrand and McCarthy, 2024). The logic behind using $EXEY$ is that if a stock has an earnings yield higher than the risk-free rate, the stock is relatively cheap, i.e., has a relatively low P/E ratio. Ben-David and Chinco (2024) provide evidence that high values of $EXEY$ are a strong predictor of buybacks, and low values of $EXEY$ predict issuance, validating its use as a measure of a stock's relative valuation relevant for firm decision making.

To simplify the interpretation, we construct an indicator variable for whether the excess earnings yield is positive $\mathbb{1}_{EXEY_{i,t}>0}$. We then augment our baseline OLS regression with $\mathbb{1}_{EXEY_{i,t}>0}$ and an interaction term between $\mathbb{1}_{EXEY_{i,t}>0}$ and Index Fund demand:

$$q_{i,j,t} = \beta_j \cdot q_{i,IDX,t} + \gamma_j \cdot \mathbb{1}_{EXEY_{i,t}>0} + \psi_j \cdot q_{i,IDX,t} \times \mathbb{1}_{EXEY_{i,t}>0} + \rho_t + e_{i,j,t}, \tag{9}$$

where ρ_t are a set of year-quarter fixed effects to account for the common time-series component in $EXEY$. The key term of interest here is ψ_j, which indicates how our groups j adjust their behavior in response to the stock being relatively cheap.

Table 5 contains the results. Our primary focus is on column 9, which contains the results for Firms. There, we see that, as in our baseline results, β_j is negative. The coefficient on γ_j is positive, consistent with the notion that when the stock is cheap, the Firm will unconditionally want to do more buybacks/less issuance (Ben-David and Chinco, 2024). Finally, the interaction term ψ_j is negative, suggesting that when the stock is cheap, the firm trades less against passive demand. In terms of magnitudes, suppose we call stocks with positive excess earnings yield "value stocks," as their earnings are high relative to the market value of the firm. Value stocks typically do not issue equity because their equity valuation is relatively lower, and therefore it is usually cheaper to raise financing in debt markets. The level effects are on the same scale as the interaction term, so combining the two effects implies that additional Index Fund demand is half of the effect of switching from being a value stock to a growth stock. Our interpretation is that Firms do not want to accommodate Index Fund demand by issuing equity when prices are relatively low.

Next, we focus on Short Sellers in column 8. As in the baseline OLS results, β_j is negative. However, the coefficient on γ_j is positive. This suggests that Short Sellers are less likely to accommodate Index Fund buying when stocks are cheap. Similar to the Firms results in column 9, this is in line with the mechanism we have in mind: Short Sellers do not want to short when prices are already low.

Table 5: Earnings Yield and Market Clearing

	Act. Funds (1)	Oth. Funds (2)	Pension (3)	Insurance (4)	Fin. Inst. (5)	Insiders (6)	Other (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.238***	0.0938***	0.0243***	0.0628***	0.0349	-0.0759***	-0.249***	-0.269***	-0.859***
	(0.029)	(0.017)	(0.003)	(0.008)	(0.068)	(0.009)	(0.070)	(0.039)	(0.066)
$1_{EXEY_{i,t}>0}$	-0.112***	-0.0167*	-0.0227***	-0.0247**	-0.290***	-0.00582	-0.653***	0.0374	1.088***
	(0.023)	(0.009)	(0.005)	(0.010)	(0.062)	(0.009)	(0.081)	(0.035)	(0.082)
$q_{i,IDX,t} \times 1_{EXEY_{i,t}>0}$	-0.106***	-0.0081	-0.00755***	0.00298	-0.512***	0.0137	0.0566	0.120***	0.441***
	(0.035)	(0.032)	(0.003)	(0.012)	(0.056)	(0.009)	(0.066)	(0.028)	(0.062)
Observations	146,874	146,874	146,874	146,874	146,874	146,874	146,874	146,874	146,874
R-squared	0.007	0.012	0.005	0.007	0.01	0.004	0.008	0.011	0.073
Fixed-Effects					YQ				

Notes. The table provides estimates from our baseline OLS regression augmented to account for the effect of relative valuation on each groups' response to Index Fund demand. We estimate

$$q_{i,j,t} = \beta_j q_{i,IDX,t} + \gamma_j 1_{EXEY_{i,t}>0} + \psi_j q_{i,IDX,t} \times 1_{EXEY_{i,t}>0} + \rho_t + e_{i,j,t},$$

where $EXEY_{i,t}$ is firm i's excess earnings yield in year-quarter t, defined as the difference between the firm's trailing 12-month earnings yield and the risk-free rate, as measured by the yield on 10-year Treasuries. ρ_t are a set of year-quarter fixed effects. Standard errors are double clustered at the stock and year-quarter level. See Section 5.1 for more details on the table.

Finally, if when prices are low, Short Sellers and Firms play a smaller role, a natural question is: which of our groups takes on a larger role to clear the market for Index Fund demand? As column 5 shows, Financial Institutions (e.g., Hedge Funds, Broker Dealers) end up playing a large part in clearing the market for marginal passive demand when prices are low. While the β_j (i.e., unconditional responsiveness) is close to zero, the γ_j is -0.512, suggesting that when prices are low, Financial Institutions are more likely to take the other side of Passive Demand. It is important to note that in this regression, we are not conditioning on the observed contemporaneous change in prices. So, it is possible that when prices are low, prices need to move more than usual to get Financial Institutions to step up and clear the market for Index Fund demand.

Excess earnings yield ($EXEY_{i,t}$) is just one measure of the relative valuation of a stock. Another valuation metric known to predict investment, and thus issuance, is Tobin's Q. Van Binsbergen et al. (2023) show that high-Q firms respond more to mispricing – e.g., through equity issuance – than low-Q firms. Their proposed mechanism is that high Q firms want to scale up investment/assets, while low-Q firms want to divest but cannot due to more severe adjustment frictions (i.e., it is easier to scale up firm assets than to scale them down).

To explore how Tobin's Q affects our baseline market clearing results, we estimate the following regression:

$$q_{i,j,t} = \beta_j \cdot q_{i,IDX,t} + \sum_g \gamma_{j,g} \cdot \mathbb{1}_{QQ=g,i,t-1} + \sum_g \psi_{j,g} \cdot \mathbb{1}_{QQ=g,i,t-1} \cdot q_{i,IDX,t} + \rho_t + e_{i,j,t}, \tag{10}$$

where $\mathbb{1}_{QQ=g,i,t-1}$ is an indicator variable that equals 1 if stock i is in Tobin's Q quintile g at the end of quarter $t-1$. Tobin's Q is defined as the inverse of the book-to-market ratio from the

Table 6: Tobin's Q and Market Clearing

	Act. Funds. (1)	Oth. Funds. (2)	Pension (3)	Insurance (4)	Fin. Inst. (5)	Insiders (6)	Other (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.119***	0.0590***	0.0187***	0.0617***	-0.176***	-0.0675***	-0.232***	-0.227***	-0.555***
	(0.022)	(0.009)	(0.003)	(0.005)	(0.065)	(0.010)	(0.051)	(0.027)	(0.049)
$q_{i,IDX,t} \times 1_{QQ=1,i,t-1}$	0.00913	-0.0195**	0.00578	-0.0105	0.0168	0.0145	-0.217***	0.0139	0.187***
	(0.023)	(0.008)	(0.004)	(0.007)	(0.056)	(0.014)	(0.074)	(0.026)	(0.064)
$q_{i,IDX,t} \times 1_{QQ=2,i,t-1}$	0.026	-0.00359	0.00434	-0.00697	-0.0169	0.0151	-0.0931**	-0.0108	0.0860**
	(0.020)	(0.006)	(0.003)	(0.007)	(0.046)	(0.012)	(0.042)	(0.019)	(0.042)
$q_{i,IDX,t} \times 1_{QQ=4,i,t-1}$	0.102***	0.0169**	0.0111***	0.00627	0.157***	-0.0401**	0.0701	-0.125***	-0.199***
	(0.023)	(0.008)	(0.003)	(0.006)	(0.055)	(0.015)	(0.055)	(0.021)	(0.059)
$q_{i,IDX,t} \times 1_{QQ=5,i,t-1}$	0.169***	0.0251***	0.0144***	0.0191***	0.332***	-0.0811***	0.043	-0.141***	-0.381***
	(0.026)	(0.009)	(0.003)	(0.007)	(0.059)	(0.018)	(0.063)	(0.027)	(0.062)
Observations	166,785	166,785	166,785	166,785	166,785	166,785	166,785	166,785	166,785
Constant	0.024	0.105	0.045	0.036	0.053	0.014	0.041	0.082	0.05
Fixed-Effects	YQ + Tobin's Q Quintile								

Notes. The table provides estimates from our baseline OLS regression augmented to account for the effect of Tobin's Q on each groups' response to Index Fund demand:

$$q_{i,j,t} = \beta_j \cdot q_{i,IDX,t} + \sum_g \gamma_{j,g} \cdot \mathbb{1}_{QQ=g,i,t-1} + \sum_g \psi_{j,g} \cdot \mathbb{1}_{QQ=g,i,t-1} \cdot q_{i,IDX,t} + \rho_t + e_{i,j,t},$$

where $\mathbb{1}_{QQ=g,i,t-1}$ is an indicator variable that equals 1 if stock i is in Tobin's Q quintile g at the end of quarter $t-1$. The middle group i.e., $QQ = 3$ is the omitted category. ρ_t are a set of year-quarter fixed effects. Standard errors are double clustered at the stock and time (year-quarter) level.

WRDS financial ratios suite, and Tobin's Q quintiles are formed each quarter. The middle group, i.e., $QQ = 3$ is the omitted category. ρ_t are a set of year-quarter fixed effects. Standard errors are double clustered at the stock and year-quarter levels. The key coefficients of interest are the $\psi_{j,g}$ which show how each group j's response to passive demand changes depending on its Q.

Table 6 presents the results. We find that, consistent with our results in Table 5, the supply side's response depends strongly on relative valuations. Focusing first on Firms in the 9th column, we show that low Q (i.e., value) firms respond significantly less to Index Fund demand than the average stock, while high Q (i.e., growth) firms respond significantly more than the average stock. In fact, there is a monotonic relationship between Q and how responsive a firm is to Index Fund demand. In terms of magnitudes, a firm in the bottom quintile of Q responds 33% less to Index Fund demand than a firm in the middle quintile of Q, while a firm in the top quintile of Q responds almost 70% more.

Turning to Short Sellers in the 8th column, we see a qualitatively similar pattern. Both the results for Firms and Short Sellers are consistent with our proposed mechanism in 5.1: the supply side is much more willing to sell into inelastic demand shocks when valuations (i.e., Q) are relatively higher. This is also consistent with results in Van Binsbergen et al. (2023) who show that high-Q firms respond more to mispricing than low-Q firms.

In summary, Tables 5 and 6 show that Firms are significantly less responsive to Index Fund demand when valuations are low. Further, out of all our investor groups, Firms adjust how they accommodate passive demand the most in response to their relative valuation. To further understand the role of relative valuations, in Appendix C.5, we replicate the results in Tables 5 and 6, splitting the sample on whether Index Funds are net buyers or sellers. We find that effects of differences in relative valuations on Firm responsiveness are concentrated in Firms' tendency to accommodate Index Fund *buying* through issuance when valuations are relatively high. The concentration of these results in the net Index Fund buying sample is perhaps unsurprising, as when valuations are low and Index Funds are selling, Firms may lack the capital needed to take advantage of low prices through buybacks. Collectively, this evidence is consistent with the narrative of Firms acting as the marginal arbitrageur in their own shares: accommodating inelastic demand exactly when prices appear to make it advantageous to do so.

5.2 Ruling out the Mechanical Channel and Reverse Causality

As discussed above, our IV results suggest that an omitted variables problem is not driving our baseline OLS results. In addition, our IV utilizes flows, which are not prone to the reverse causality concern that index funds mechanically buy and sell in response to issuance and buybacks, respectively. Because of the mechanical nature of the reverse-causality problem in our setting, we provide more context and additional reasons for why reverse-causality is unlikely to be the main driver of our findings.

To clarify what the mechanical index response is to firm activity, consider the following numerical example. Suppose that there is only one passive fund, which is a value-weighted index fund that holds the entire market. For simplicity, assume that this fund applies no float adjustments and has enough AUM such that it holds 10% of each constituent firm's shares outstanding. Now, suppose one firm conducts an issuance equal to 5% of its shares outstanding, while all the other firms do neither net issuance nor net buybacks. This will trigger trading by the value-weighted index fund, as it must maintain a constant ownership percentage of the shares outstanding of each constituent (Sammon and Shim, 2023).[18] To do this, the fund must buy shares of the firm that issued, which it will fund by selling shares of everything else.

In this case, the fund will need to buy roughly 10% of the issued shares, i.e., 10% $\times$ 5% = 50 bps of shares outstanding.[19] Then, the "beta" in this example from our baseline regression of Firm

[18]This logic would also apply if we considered the *float-adjusted* shares outstanding of each constituent. Float adjustment are one reason why the holdings of capitalization-weighted index funds deviate from the value-weighted portfolio that the academic literature often constructs.

[19]To see this, suppose the firm initially had 100 shares outstanding, so after the issuance, if the value-weighted index fund didn't trade, it would own 10/105 = 9.5% of shares outstanding. By buying 10% of the issuance, the fund would own 10.5/105 =10% of the firm's shares outstanding. We say "roughly" here because this is actually a fixed-point problem for the fund. Specifically, the fund will need to determine the right amount of all the other stocks to sell such that it will hold a constant percentage of each firm's share outstanding while respecting the constraint of fully investing its AUM – and as a result will buy less than 10% of the issuance, as after selling the other stocks to "make room" for the issuance, it will own less than 10% of their shares outstanding.

demand on Index Fund demand would be -5% = $\beta\times$ 0.5%, i.e., $\beta = -10$.

The exact problem that might cause concern is as follows: Suppose most of the time, Firms do not respond to Index Fund demand. But, sometimes Firms act in the primary market and Index Funds mechanically respond. Then we would be mixing "betas" of -10 with "betas" of 0 and we end up recovering a number like -0.6, i.e., our baseline OLS estimate.

To rule out this mechanism as the main driver of our findings, we have already shown our IV results, which at least partially rule out the mechanical story. This is because our IV is designed to isolate the part of Index Fund demand coming from *flows*, as opposed to mechanical rebalancing in the face of changes in shares outstanding due to Firm activity.

In this subsection, we discuss several additional pieces of evidence for why we believe the mechanical/reverse causality story is not the main driver of our results. First, as highlighted in the example above, the mechanical effect is proportional to -1 times the inverse of lagged passive ownership. As passive ownership has increased, therefore, the part of the "beta" coming from the mechanical response should have shrunk in absolute value. So, if the mechanical trading of Index Funds was entirely driving our findings, our β_{Firm} should be steadily approaching 0 over time (because the mechanical beta magnitude is 1 over fraction of passive ownership, and passive ownership has increased significantly). Figure 12 in Appendix B.7 shows the opposite – β_{Firm} has become more negative over time, inconsistent with the mechanical channel as the primary driver of our results.

Another important aspect of the mechanical story is that it should be symmetric with respect to issuance and buybacks. Going back to our numerical example, if the Firm bought back 5% of shares, the value-weighted index fund would be forced to sell roughly 50 basis points of the firm's shares outstanding. However, Figure 4 shows that our effect is asymmetric, with Firms primarily responding to Index Fund demand when Index Funds are net buyers. Again, this is inconsistent with the mechanical effect entirely driving our results.

These three points help rule out the mechanical story as the primary driver of our results. We do caveat that the mechanical effect is present in some form in our data – many index funds are required to buy after issuance and sell after buybacks. However, how this is actually implemented by index funds is nontrivial and amounts to a fixed-point problem. For example, if many firms issue shares in a given quarter (and as we show in Figure 15 and describe in Appendix D.1, about 70% of Firms in each quarter issue shares on a net basis), then the amount that an index fund buys is a function of the relative sizes of issuance/buyback activity and when the index it tracks reflects these adjustments. To see how difficult it is to predict what the mechanical effect is in a precise way, in the absence of flows, if all of the stocks held by an Index Fund issue shares, then the Index Fund will buy more shares from Firms that did the most issuance and *sell* shares of the Firms that issued but did less issuance as a percentage of shares outstanding. These adjustments are further complicated by the timing of index adjustments, which can range from immediate adjustment within a few days, to end-of-quarter adjustments. Further, many index funds do not hold a value-weighted portfolio based on float-adjusted capitalization (e.g., equal-weighted funds or funds that impose a floor and/or ceiling on the weight of holdings), and for such funds mechanical trading in the face of issuance/buybacks would need to be determined on a case-by-case basis. For these reasons, it is difficult to construct proxies which precisely isolate the mechanical component of buying and selling by Index Funds and is beyond the scope of this paper.

5.3 Decomposing Firm Changes

We decompose Firm changes into three sources: Buybacks, SEOs, and other sources. We identify the quarterly total dollar value of buybacks using PRSTKCY in Compustat – which we convert into share terms by assuming that Firms buy back at the volume-weighted average (split-adjusted) price over the quarter. We hand collect data on SEOs from Bloomberg for 2010 onward. This includes all types of Seasoned Equity Offerings, including, e.g., those which go through the traditional book-building process, at-the-market offerings and privately placed block sales. We Winsorize buybacks at the 99% level and SEOs at the 1% level (because buybacks are always positive and SEOs are always negative). All other sources of shares outstanding changes are accounted for by the remainder. This gives us three measures of Firm activity to replace our single measure that we have used throughout the paper. Two of these measures capture direct activity from Firms (buybacks and SEOs). We think of the remainder as mainly capturing compensation (i.e., stock directly awarded as compensation, restricted or performance stock units – RSUs or PSUS – or exercised stock options), but it may also include other ways in which shares can be created (e.g., the exercise of warrants or convertible debt).[20]

As in Section 2.2.2, we construct the $q_{i,j,t}$ variables so that a positive value represents Firms buying shares and a negative value corresponds to selling shares (i.e., issuance). Also as before, the $q_{i,j,t}$ variables are represented as a percentage of shares outstanding. In these tests, we utilize a longer year-over-year horizon because of the irregular nature and large size of SEOs, coupled with the stale data issues of CRSP shares outstanding described in Section 2.1.[21] These factors may cause the residual Firms group to capture more timing issues instead of compensation and other sources of issuance.

Table 7 presents the regression estimates. It shows that compensation and other sources account for the vast majority of Firm responsiveness to Index Fund demand, with an estimate of -1.2 (and

[20]The CRSP data on shares outstanding does not include treasury shares. This means that if shares are held in the treasury stock but are slated to be awarded to employees, they will only be counted into shares outstanding once they are actually awarded.

[21]For example, if there is an SEO at the end of a quarter, it may not be reflected in CRSP shares outstanding till the next quarter. And, since our three groups are a decomposition of Firm demand, if there is an SEO that results in issuance of 10pp, it may cause the residual Firms group have a close to 10pp positive demand this quarter and a -10pp negative demand the following quarter when CRSP shares outstanding are updated to reflect the SEO.

Table 7: Beta Estimates (2010-2021): Decomposing Firm Changes

	No FEs		Ind. x YQ FE	
Investor Group	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$
Active Funds	0.463	7.377	0.458	6.158
Other Funds	0.184	5.397	0.142	12.756
Pension Funds	0.043	5.104	0.044	5.409
Insurance	0.116	10.368	0.110	11.933
Financial Institutions	0.777	4.309	0.876	6.049
Insiders	-0.288	-5.173	-0.339	-5.667
Other	-0.444	-2.457	-0.544	-2.554
Short Sellers	-0.352	-12.787	-0.371	-17.595
Firms (Buybacks)	-0.181	-9.932	-0.148	-8.102
Firms (SEOs)	-0.119	-8.661	-0.109	-7.048
Firms (Compensation, Other)	-1.200	-12.934	-1.120	-11.333
Total	-1.001		-1.001	

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. We decompose our Firms group into three new components: seasoned equity offerings (SEOs), buybacks, and compensation and other issuance activity. We estimate the set of regressions with no fixed effects (left columns) and with Fama-French 10 industry-by-year-quarter fixed effects. The unit of observation is stock-year-quarter, $q_{i,j,t}$ are measured on a year-over-year basis and the data covers the time period 2010 to 2021. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level and we control for autocorrelation up to 6 lags due to partially overlapping data.

-1.12 with industry-by-quarter fixed effects). Since the sum of the three Firm betas must equal the overall Firm beta, we can attribute about 80% of Firms clearing the market for passive demand to things like stock compensation, conditional stock compensation (like RSUs and stock options), warrants, or convertibles. The other two groups, buybacks and SEOs, have similar beta estimates to each other between -0.1 and -0.2, but much smaller than the compensation and other issuance group. All three groups are negative, suggesting that all three contribute to clearing the market for passive demand.[22] In addition, given the role that compensation is likely to play, a natural question is whether our findings are dominated by a few industries (e.g., the tech sector) that tend to use stock as a source of compensation. In Appendix B.6.1, we show that, while there is variation in Firms' betas by industry, all industries have a negative beta.

Another pattern we have documented is that Firms are particularly responsive to buying, as opposed to selling, by Index Funds. We show in Sections 3.1.2 and 3.1.3 that the slope between Firm and

[22]The smaller buybacks coefficient could also be because buybacks tend to be conducted by a minority of Firms and the average size (as a fraction of total shares outstanding) tends to be smaller. See Appendix D.1 for stylized facts on buybacks. Further, if we restrict to the sample of firms with a buyback program in place – defined as firms with positive values of PRSTKCY over each of the previous 4 quarters – the coefficient on buybacks nearly doubles to -0.36 (see Appendix D.2). This is consistent with the fact that – as we show in Appendix D.1 – only a subset of firms seem to have a buyback program in place, and a nonexistent buyback program cannot be adjusted in the face of passive demand.

Index Fund demand is much steeper in firm-quarters with net Index Fund buying and estimate that it is nearly -1. This is unlikely to be a coincidence. Shares issued for the purpose of employee compensation are likely to have an option-like structure: shares awarded to employees increase when prices are high, and employees are more likely to exercise their options when recent returns have been high (Heath et al., 1999). A similar argument can be made with convertible debt and warrants. And, according to the evidence in Section 4, Firms clear the market for Index Fund demand using prices as a coordinating device.

This suggests that Firm issuance through compensation and other sources should be much more sensitive to passive buying than selling. Similar to the tests in Section 3.1.3, we split the sample based on whether Index Funds were net buyers or sellers in a stock-quarter. Table 8 provides the regression estimates. We find that more than 80% of all issuance that clears the market for passive demand is from compensation and other issuance, with SEOs and buybacks playing a role, albeit a small one, similat to the unconditional results in Table 7. The Firms compensation beta dwarfs all other betas for positive demand, similar to what we found in the unconditional results. For negative Index Fund demand, we find that all three Firm betas are positive, and the largest of the three is compensation. First, this suggests that even when Index Funds are selling, Firms are issuing some shares for compensation, though the magnitude is much smaller than when Index Funds are net buyers. Second, none of the three Firms group contribute to clearing the market for negative Index Fund demand. In fact, all beta estimates are positive or close to zero when passive funds are selling. Nearly all of the market clearing in this sample comes from the residual Other group, representing retail investors, small institutions, and other investors not captured by our data.

These results point to the primary source of Firm responsiveness as coming from compensation and other issuance, not from buybacks and SEOs. This is helpful in connecting our results on Firms clearing the market for passive demand and conventional wisdom that SEOs are large but rare. In addition, ruling out SEOs and buybacks as the main source of Firm responsiveness helps rule out reverse causality stories, which are mainly a function of primary market activity, and are complimentary to Sections 4 and 5.2.

5.4 What Goes into Firm Issuance?

The last subsection shows that most of Firms' responsiveness comes from sources outside of buybacks and SEOs. Through examining dozens of individual 10-K filings, we observe that the source of issuance most prevalent is some form of stock-based compensation, either through direct stock grants, or through restricted stock units (RSUs), performance stock units (PSUs), Employee Stock Option Programs (ESOPs), or Employee Stock Purchase Programs (ESPPs).

To get a sense of how much compensation accounts for the residual part of Firm activity (i.e., Firm activity that is not explained by buybacks and SEOs), we use the variable `stkco` in Compustat,

Table 8: Regression Estimates (2010-2021): Decomposing Firms by Index Fund Demand Direction

	Negative Demand		Positive Demand	
Investor Group	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$
Active Funds	0.529	2.095	0.519	7.089
Other Funds	0.112	2.859	0.204	5.736
Pension Funds	0.065	2.481	0.044	4.064
Insurance	0.113	3.665	0.122	9.357
Financial Institutions	1.123	1.580	0.890	4.231
Insiders	-0.109	-1.749	-0.316	-4.591
Other	-3.068	-2.490	-0.129	-0.729
Short Sellers	-0.244	-2.594	-0.393	-11.876
Firms (Buybacks)	0.118	1.616	-0.164	-10.202
Firms (SEOs)	0.019	3.155	-0.158	-7.309
Firms (Compensation, Other)	0.341	3.800	-1.622	-10.861
Total	-1.001		-1.003	

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\mathrm{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. We decompose our Firms group into three new components: seasoned equity offerings (SEOs), buybacks, and compensation and other issuance activity. We estimate the set of regressions separately for observations where Index Funds were net sellers in a stock (left columns) and net buyers (right columns). The unit of observation is stock-year-quarter, and the data covers the time period 2010 to 2021. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level and we control for autocorrelation up to 6 lags due to partially overlapping data.

which captures "stock compensation expense," and includes stock bonuses, deferred compensation, and stock-based compensation. We refer to this variable as *compexpense* going forward. Importantly, *compexpense* does not include issuance from vested RSUs and PSUs, exercised options from ESOPs, or stock issued through ESPPs. We refer to stock issued through these programs as *compcond*, since it often has a conditional nature based on a combination of share price, company performance, and vesting period.

We proceed in two steps. First, we examine SEC filings to capture data on RSUs, PSUs and ESOPs to identify the degree to which *compexpense* is statistically related to *compcond*. This also allows us to assess the magnitude of *compexpense* and compare it with the typical magnitude of *compcond*. To this end, we scrape 10-K filings and examine a subset of the data we collect with non-missing and non-zero values for RSUs, PSUs, or ESOPs to construct a *compcond* measure. We then apply a series of data-quality filters and perform manual validation with actual filings to ensure that *compcond* is accurate.

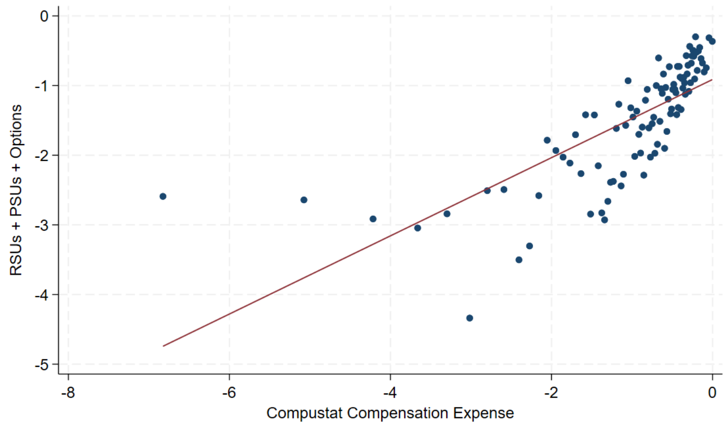
Specifically, we restrict to stock-quarters where *compcond* is above the 1st percentile for our residual Firm category (i.e., we remove observations which appear to be data errors), stocks for which we can successfully scrape at least 3 10-Ks, and to stocks with a correlation above 0 between our residual Firms category and (*compcond*+*compexpense*). This is primarily to combat issues where the scraped data from filings appears to be incorrect by many orders of magnitude due to errors in scraping the proper units.[23] While the resulting sample is small and is skewed towards larger-cap stocks, we find that our main results on Firm issuance clearing the market for passive demand also hold for this subset of observations.

In the second step, we use *compexpense* as a proxy for overall compensation and examine how it relates to our residual Firms group, i.e., the part of Firms demand unexplained by SEOs and buybacks. We avoid a further decomposition of our residual Firms group into different types of compensation for two reasons. First, as outlined above, *compexpense* misses a significant source of issuance – namely, the compensation captured in *compcond* – especially the type that is likely to be the most responsive to prices. Second, our residual Firms group soaks up any data errors or timing issues associated with when SEOs and buybacks are reflected in shares outstanding in CRSP.[24] In both steps of our analysis, we focus on annual data using company fiscal years due to data consistency and availability.

[23] More precisely, this units issue arises when some filings for a company have units properly adjusted and others do not. This creates, for example, a situation where a company will have 1,500,000 RSU shares vested in one quarter and 1,500 RSU shares vested in another. When instead considering value-weighted averages, this last correlation-based filter is less important, as many of the outliers are driven by small firms.

[24] In general, CRSP records changes in shares outstanding with a delay and many of the timing errors will increase the volatility of the residual group because it may have to offset SEOs or buybacks that occurred (as recorded by our SEO and buyback data) but are not yet reflected in shares outstanding. All of our results are robust to dropping observations where we appear to have one of these stale-data issues, that would manifest, e.g., as a large issuance in quarter t due to an SEO accompanied by an offsetting contemporaneous positive entry for our residual Firm category and a large negative value for the residual Firm category in the following quarter when shares outstanding is eventually updated by CRSP.

Figure 5: Conditional Stock Compensation (*compcond*) vs. Stock Compensation Expense (*compexpense*)



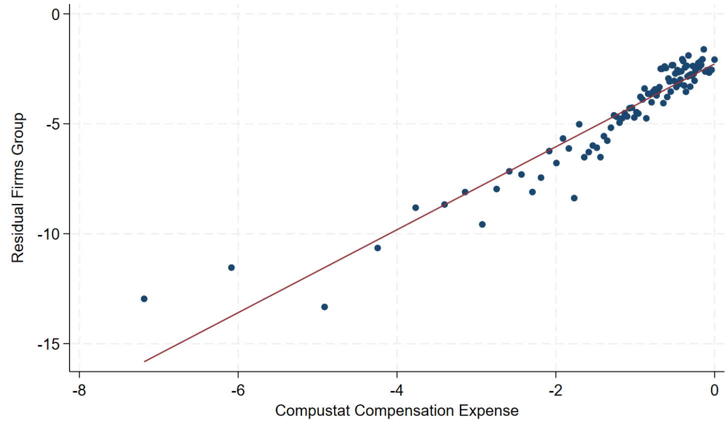
Notes. This figure presents a binscatter plot of our *compcond* variable against *compexpense* (`stkco` in Compustat), both expressed as a percentage of shares outstanding. *compcond* is constructed using the sum of vested RSUs, vested PSUs, and exercised stock options from a subset of scraped filings. Both groups use annual data based on fiscal years. See Section 5.4 for more details.

Figure 5 presents the statistical relationship between *compexpense* and *compcond* for the subset of observations that pass the data quality filters described above. We can see that they are strongly related to each other, with a slope of 0.56 and a correlation of 18%. This suggests that *compexpense* is picking up the firm quarters where *compcond* is also an important source of changes in shares outstanding.

Given how closely related *compexpense* and *compcond* are in our subset, we use *compexpense* as a proxy for overall stock compensation for our full sample of stocks, i.e., we do not apply the filters described above based on the scraped 10-K data. Figure 6 provides a binscatter plot of our residual Firms group against *compexpense*. The estimated slope from a univariate regression of our residual Firms group on *compexpense* is 1.79, with a correlation of 23%. The magnitude of the estimated slope is reasonable given the slope of 0.56 from a regression of *compcond* on *compexpense* – *compexpense* is missing the additional issuance from *compcond*. Perhaps more importantly, the magnitudes of Figures 5 and 6 jointly suggest that stock compensation drives most if not all of the residual Firm activity not explained by buybacks and SEOs. That is, if adding *compcond* to *compexpense* roughly doubles the magnitude of total stock compensation (as seen in Figure 5), then the residual Firms group is, on average, one-for-one with total stock compensation.

While this analysis missed the full set of stocks and dates (in Figure 5) and all the sources of conditional compensation data (in Figure 6, the combination of these two results point to employee compensation as the biggest source of shares when passive investors demand shares.

Figure 6: Residual Firm Activity vs. Stock Compensation Expense



Notes. This figure presents a binscatter plot of our residual Firms group against *compexpense* (`stkco` in Compustat), both expressed as a percentage of shares outstanding. Both variables use annual data based on fiscal years. See Section 5.4 for more details.

6 Conclusion

We answer a basic question: Who sells when passive investors buy, and who buys when passive investors sell? That is, when passive investors trade, who ultimately clears the market? Our main finding is that Firms have been the single most significant provider of shares purchased by Index Funds. We estimate that when passive investors demand 1pp more of Firms' shares outstanding, Firms respond at rate of 0.64 percentage points more shares issued/fewer shares repurchased. Short sellers are another important group for market clearing, with a response coefficient of -0.24. These two groups alone account for 88% of the marginal shares needed to clear the market in the face of additional passive demand. Conditional on Index Fund buying, Firms alone provide nearly all of the shares, i.e., they sell at nearly a one-for-one rate to passive purchases. Firms, however, do not play a role in clearing the market when Index Funds are net sellers of a stock, which is where Financial Institutions and our residual group (composed of small institutions and retail investors) together clear the market for passive demand. In the long run, all demand-side groups, including Financial Institutions, mimic the direction of passive demand: they buy more/sell less in the stocks that passive investors buy more of (and vice versa when passive investors sell more).

Our proposed mechanism is that prices coordinate market clearing. To test this, we construct an instrument for inelastic Index Fund demand designed to be orthogonal to own-firm fundamentals. Specifically, we identify stocks which are expected to receive passive inflows or outflows because of the combined of effect of returns in unrelated stocks in the same index fund and return-chasing behavior by index fund investors. We obtain strikingly similar results in this better identified setting, evidence that Index Fund demand *causes* Firms to issue equity. In addition, our instrument identifies a significant source of inelastic demand by index funds and ETFs that is proportional to and mimics overall passive demand, and retains the breadth of the entire U.S. equity market. This is in contrast to the common practice of using index additions and deletions to identify passive demand shocks, which, while well identified, are narrow in scope. We also provide direct evidence that prices are the coordinating device which leads Firms to clear the market for Index Fund demand. We find that Firms are much more likely to issue in response to high prices using excess earnings yield and Tobin's Q as proxies of relative valuations. More broadly, our findings suggest that Firms are systematically more active in secondary equity markets than previously understood.

Lastly, we trace the sources of Firm responsiveness by decomposing Firm demand into three groups: buybacks, SEOs, and other Firm issuance, which contains sources like stock issued for compensation and from the exercise of warrants or conversion of convertible debt. We show that most of the responsiveness comes from these other sources. Primary market activity, like buybacks and SEOs, are either regularly scheduled or are rare occurrences, consistent with other, more dynamic sources of issuance being the most responsive to passive demand. We provide additional supporting evidence that the other sources of Firm issuance strongly resemble a combination of stock compensation and conditional stock compensation (from, for example, exercised stock options and vested RSUs and PSUs). This sheds more light on not only how pivotal firms are in providing shares to satisfy demand, but also that the ways in which firms take this action is through sources that have not been studied in connection with asset pricing.

One way to interpret our collection of findings is that Firms are more elastic than large institutional investors. This has implications and provides potential new avenues for the growing literature using demand-system asset pricing models (Koijen and Yogo, 2019), which hold the supply side fixed. Incorporating the supply side in demand-system asset pricing models is a promising area of future research.

More broadly, because Firms respond to inelastic passive demand through prices, our results suggest that Firms are likely to respond to any positive inelastic demand shock that affects prices, not just passive demand shocks. This is the sense in which our results, and specifically our IV, work as a laboratory to study which groups respond most strongly to inelastic demand shocks in general.

Our findings also have important implications for corporate finance in that they suggest that passive ownership can have real effects on firms, including for capital structure, payout policy, and investment policy. As discussed in Morck et al. (1990), there are many reasons why the stock market is more than just a sideshow and may matter for the real economy. We provide evidence on a particular channel, specifically that passive ownership may affect firms' financing decisions. Our findings show that firms respond to increased inelastic demand by issuing more equity. And, given our evidence that prices coordinate market clearing, this suggests that Firms are issuing at relatively high prices, taking advantage of a perceived lower cost of capital.

Moreover, the fact that Firm responsiveness works through compensation, and possibly other non-primary-market offerings, provides insight on the breadth and scope of ways in which Firms can issue shares. This, in and of itself, is interesting, but also points to several promising questions for future research: If stock awards are a growing part of compensation (Eisfeldt et al., 2023a) and inelastic demand triggers stock awards which ultimately end up in the hands of index funds, is the growth of passive ownership related to changes in the level and distribution of the labor income share? Can firms utilize employee compensation to raise capital when constrained, preserving cash today by substituting wages for future equity?

We end with a puzzle: while we find strong evidence that Firms provide shares for positive inelastic demand shocks, we find that no large institution nor the firms themselves buy when Index Funds are selling. In our data, our residual Other category, which represents small institutions, retail investors, and some foreign investors, is the primary buyer of shares when Index Funds (and nearly all other groups, which mimic Index Funds) sell shares. This begs the question, who exactly is buying shares that seemingly everybody wants to sell, and why do large institutions systematically avoid buying these stocks?

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Who Clears the Market When Passive Investors Trade?

Marco Sammon and John J. Shim

INTERNET APPENDIX

A Data and Methodology Appendix

A.1 Data Sources and Cleaning Details

In this appendix, we provide greater detail on the the data sources and cleaning decisions, which were outlined in Section 2.1.

A.1.1 Thomson Reuters S12 13F Holdings Data

We use the Thomson Reuters S12 data for mutual holdings data for all funds registered under the Investment Company Act of 1940 (commonly referred to as 40 Act Funds). These are mostly mutual funds, exchange-traded funds (ETFs), closed-end funds, and unit-investment trusts.

We separate all funds into three categories: Index (passive), Active, and Other. We classify a fund as an Index Fund based on the index fund flag and the fund name in the CRSP mutual fund database using the method in Appel et al. (2016).[25] We classify a fund as Active if it is in the universe of funds that can be linked between the CRSP mutual fund dataset and the Thomson S12 dataset using the WRDS MF links database but it is not otherwise classified as passive. Any remaining funds that cannot be matched between Thompson and the CRSP mutual fund database are included in a separate "Other Funds" group. It is worth highlighting that an update to the S12 data, which took place in February 2022 and retroactively updated previous S12 data, dramatically increased the size of the Other Funds group from 2017-present, mainly coming from increased coverage of foreign funds which hold US equities.

[25] Specifically, we classify a fund as passive if it meets either of the following criteria: (1) It has a non-missing value for the index fund flag in the CRSP mutual fund database. This includes funds with code "D" (pure index funds), code "B" (index-based funds) and code "E" (enhanced index funds) (2) It has a name that makes it look like an index fund. To identify these funds, we use the same list of strings as Appel et al. (2016), which includes permutations of index names like "S&P" and "500". Although this is a less conservative definition of passive funds than used in other papers (e.g., Crane and Crotty (2018), which only includes funds with an index fund flag of "D"), including these additional funds has little effect on the level of passive ownership. For example, in 12/2022, the level of passive ownership under the Crane and Crotty (2018) definition is 16.7%, while under our definition it is 17.1%.

As discussed in Sammon and Shim (2023), the prevalence of stale filings can create problems when working with changes in holdings. To address this issue, we linearly interpolate holdings of each stock at the fund level across stale quarters, for up to three consecutive stale quarters.

A.1.2 Thomson Reuters S34 Mutual Fund Holdings Data

We obtain data on institutional investors' holdings from 13F filings recorded in the Thomson S34 dataset. Institutions are required to file a 13F if they hold more than $100M in qualified securities. To classify institutional investors into groups, we use the 13F classification procedure in Bushee (2001), and data for the classification from Brian Bushee's website. The classification assigns each institution to one of the following categories: banks, investment companies, independent investment advisors, insurance companies, corporate pension funds, public pension funds, university and foundation endowments, and miscellaneous. When forming our groups, we combine insurance companies and university & foundation endowments into our "Insurance" group because they are both very long-horizon investors (and the endowments group is relatively small). We also combine corporate and public pension plans into our "Pension Funds" group because they have common objectives.

A.1.3 CRSP

We use the CRSP monthly stock database for data on shares outstanding. While shares outstanding is not traditionally an investor category, to do a complete accounting for how shares change hands, we also include the Firm itself (i.e., it can issue or buy back shares). We identify share issuance/buybacks based on changes in split-adjusted shares outstanding. Importantly, CRSP shares outstanding does not include treasury or authorized shares.[26] This means that stock awards which have been approved by the board of directors and even shares have been authorized/issued but held in the treasury will not be counted. Such shares will only be counted toward CRSP's definition of shares outstanding when they are actually awarded to employees (and, thus, theoretically available in the market if those employees choose to sell shares).

A.1.4 Computstat/Markit

Another potentially important source of shares is Short Sellers. Specifically, each shorted share effectively creates an additional share that needs to be held by another investor. In addition, when Short Sellers close their positions, the effective supply of shares decreases. Therefore, to get a complete accounting of how shares can change hands, we also examine changes in short interest.

[26] See the CRSP US Stock Data Description Guide (page 125) for more details.

Short interest data are obtained from Compustat following the method in Hanson and Sunderam (2014). The short interest ratio computed using Compustat data is highly correlated with the level of short interest reported by S&P Global's Markit database. We also use Markit to obtain data on the shares available for shorting, utilization rates, and shorting costs.

A.1.5 Insiders

For insiders, we do not have the level of holdings but only changes in holdings via their publicly reported buying and selling activity. We get data on insider transactions from the Thomson Reuters Insiders dataset, which we aggregate at the firm and quarter level.

A.1.6 Index Constituents Data

The next collection of datasets we leverage include information on index membership, index weights and float adjustments. We obtain S&P 500 and S&P 1500 membership data directly from S&P. Starting in 2002, this includes float adjustments for all stocks in the 1500 universe. We get data on the S&P MidCap 400 and S&P SmallCap 600 membership from Siblis Research, and match this to the S&P 1500 data to obtain float adjustments, as the same float adjustment is applied to all sub-indices within the S&P 1500 index family. We get Russell index membership data from FTSE Russell. Starting in 2008, this includes daily index membership, as well as daily float adjustments and index weights. We get Nasdaq 100 index membership from Siblis research, which starts in 2014.

We get CRSP index membership directly from CRSP. This includes daily index membership, weights and float adjustments starting in 2014 for all CRSP sub-indices. In our analysis, we pool together all CRSP index-based funds which do not track the CRSP total market index, as the AUM tracking these is small relative to the AUM in the three funds tracking the CRSP total market index (VTSAX, VTI and VITNX[27]).

We identify migrations within families of indices by identifying stocks which were simultaneously added to one index in the family and dropped from another (e.g., a stock which is dropped from the Russell 1000 and added to the Russell 2000 at the same time is classified as a Russell migration).

In addition to classifying funds based on whether they are active or passive, we also aim to identify the index each passive fund is tracking. To identify funds tracking CRSP indices, we obtain a list of fund tickers from Vanguard's website. To identify funds tracking Russell, S&P and Nasdaq

[27] Note that VITNX does not exactly track the CRSP total market index. According to Vanguard's website, "The fund replicates more than 95% of the market capitalization of the index and invests in a representative sample of the balance using a portfolio-optimization technique to avoid the expense and impracticality of full replication." This is in contrast to VTSAX and VTI, which are designed to fully replicate the CRSP total market index.

indices, we use the funds' names in the CRSP mutual fund database. For example, to identify S&P 500-tracking funds, we look for combinations of "S&P", "S & P", "SandP", "S and P", "SP" (all non-case sensitive) and "500". For the S&P 500, we validate our name-based classification by comparing it a classification based on the Lipper Objective Code "SP" (i.e., the Lipper Objective Code for S&P 500 funds). We find these two methods yield similar results, allaying concerns about misclassification using our names-based methodology. We also hand check the largest funds tracking each index to ensure they are classified correctly.

We then compute the ratio of the AUM of all funds tracking each index to the total index float (i.e., the sum of the float adjusted market capitalization of all index members). Then, at the stock level, we compute the expected number of shares held by each family of index funds as shares outstanding $\times$ AUM Tracking/Index Capitalization $\times$ IWF (where IWF is the investable weight factor, expressed as a decimal). The logic is that an index tracker – by construction – holds a constant percentage of each constituent's float (Sammon and Shim, 2023). As a specific example, suppose that S&P 500 tracking funds own 10% of the index's float. And then, consider an individual stock with a float adjustment of 0.8. S&P 500 index funds are expected to own 10% of the stock's float, i.e., $10\% \times 0.8 = 8\%$ of the firm's shares outstanding.

One concern with this method for computing expected ownership by each family of index funds is that it likely understates the true size of index trackers, as there are many investors tracking these benchmarks – e.g., direct replication by institutional investors and shadow indexing by active investors – which will not be captured by index fund holdings alone (Chinco and Sammon, 2023). Given that our market clearing exercise is based on investor type, not investor mandate, we believe this is not an issue in our setting.

Another concern with this method is that it will identify funds tracking subsets of the indices we are actually interested in, e.g., S&P 500 value funds like IVE. And, empirically, there is significant variation in passive ownership share across stocks in these subindices. That being said, we perform several validation exercises to ensure that our measure of expected buying around index change events is not biased by ignoring these sub-index classifications. The logic is that if about half the stocks added to a particular index are growth stocks, and half the stocks added to the index are value stocks, the fraction of the index's float held by index funds will still capture the average buying across these subindices and thus the average expected buying by such funds.

A.1.7 Data Filters

To be included in our sample, stocks must pass several additional filters. First, we only include ordinary common shares (CRSP share codes 10-11) traded on major exchanges (CRSP exchange codes 1-3). Second, we exclude stocks that are an acquiring CRSP Permno or have an acquiring CSRP Permno in either quarter t or quarter $t-1$. This is because in such quarters, there can be large changes in split-adjusted shares outstanding because, e.g., a firm issues shares to acquire another company, which can create extreme outliers in $q_{i,j,t}$.

Furthermore, we require that each stock is included in one of the major index families (S&P 1500, Russell 3000 or CRSP Total Market), because our primary objective is to study market clearing when index funds trade. Our index data for the S&P 1500 universe starts in 2002, our Russell index data starts in 2009, and our CRSP index data (now used by many Vanguard index funds) starts in 2015.[28] We use 2002 to 2021 as our baseline sample, as it covers most stocks in most indices and still captures the significant growth in passive ownership. As a robustness exercise, we re-estimate our baseline empirical tests in Section 3 on various time subsamples. The findings are qualitatively similar to our baseline results. We provide these additional results in Appendix B.4.

A.2 Forming Investor Groups

A.2.1 Overlapping Groups

Figure 7 provides a visual illustration of the data, and the adjustment we use to ensure the categories are mutually exclusive. In the top panel of Figure 7, the circle represents 100% which is the total number of shares outstanding in a hypothetical stock. The orange region represents the ownership of all 40-Act Funds (roughly 35% in this example) and the blue region represents all 13F institutions (roughly 75%). These numbers are roughly in line with a typical stock-quarter in our sample.

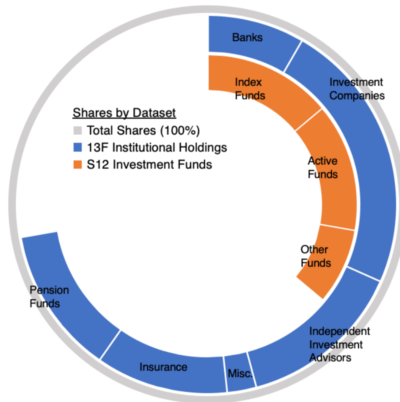
The figure also illustrates the overlap of the mutual fund and 13F datasets – nearly all of the 40-Act Fund holdings are recorded in some combination of 13F filings for banks, investment companies, independent investment advisors, and miscellaneous institutions. We combine these four 13F categories and subtract all fund holdings to create a separate category. The bottom panel of Figure 7 shows this new financial institutions category, which does not overlap with other groups. This leaves us with 6 mutually-exclusive investor groups that together sum up to total 13F institutional holdings but now with a separate accounting for index funds, active funds and other mutual funds.

The bottom panel of Figure 7 also highlights a placeholder for a residual category that represents all ownership that is outside of 13F filings. We attribute this group largely to retail investors, small and foreign institutional investors, as well as other miscellaneous sources of holdings. This is meant to provide a sense of who might account for owning the remainder of the shares of each company. We will describe this residual category in more detail in Section 2.2, where we discuss the methodology.[29]

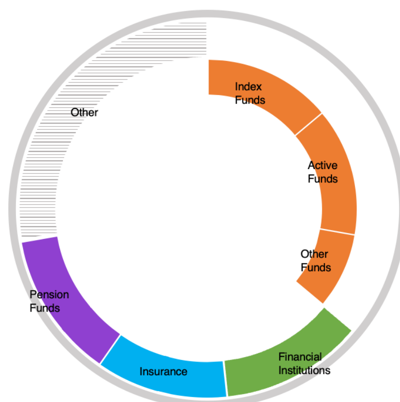
[28] Although Vanguard's transition to CRSP indices was initiated in 2012, it was not finished until 2014.

[29] It is possible that some of the Other Funds are foreign funds which are not part of institutions which file 13Fs. As we outline above, we subtract *all* the holdings in S12 filings from the 13F filings for groups known to manage mutual funds. We do this because, due to matching issues between S12 and 13F data, we cannot unambiguously determine if an S12 filing institution is part of a 13F filing institution or not. For example, VanEck's individual funds' S12s

Figure 7: Dataset Decomposition and Investor Categories: Example



Panel A: Datasets and Categories



Panel B: Mutually-Exclusive Categories

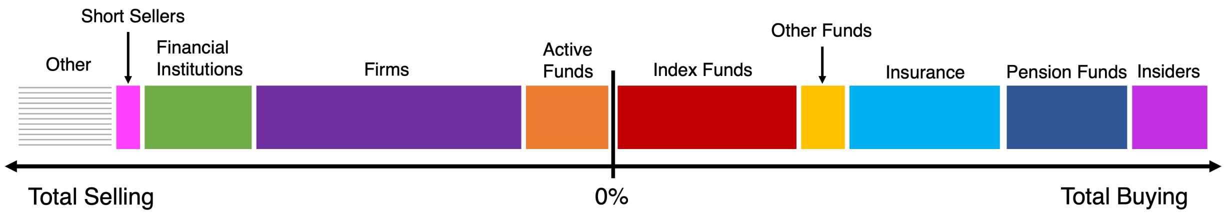
Notes. Panel A presents the fraction of the average stock's shares outstanding owned by the investor categories we can observe in the S12 and 13F data. Panel B presents the same breakdown, except the categories have been refined to be mutually exclusive.

A.2.2 Illustration

Figure 8 provides an illustrative example of what the data might look like. The figure shows each of the 10 groups and their respective share change. The quantity of the share change is represented by the block width and the direction of their share change is represented by which side of 0% they fall on. This example shows that Index Funds, Pension Funds and Insurance make up a majority

cannot be matched based on Thompson's identifiers to VanEck's overall 13F. In this case, if we assume that a lack of a match means that the S12 funds are not part of a 13F institution, we would be double counting VanEck's position changes. So, to avoid such double counting, we assume all S12 filings are also part of a 13F filing. This will prevent double counting VanEck's position changes, and thus prevent creating an erroneous offsetting change in our Other group. On the other hand, in the case of a mutual fund which is part of an institution which does not file a 13F, we will erroneously create an offsetting Other trade.

Figure 8: Share Changes by Group: Example



Notes. Example breakdown of net buying and selling by our 10 mutually exclusive investor categories. Bars above zero denote net buying, while bars below zero denote net selling. Because markets must clear, total net buying is by construction equal to total net selling.

of the buying, while Firms, Active Funds, and Financial Institutions make up a majority of the selling. The example also shows that shares changes for the first 9 groups do not clear the market, i.e., they do not sum to zero. Thus, the residual group appears on the selling side to make sure total buying equals total selling.

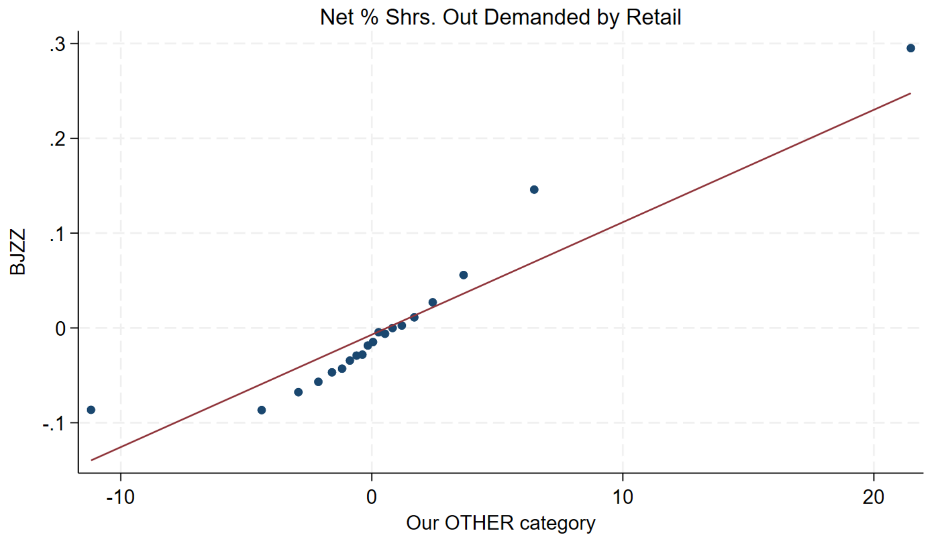
A.2.3 Residual Other Category and Retail Investors

As discussed in the previous section, we have an Other category, whose demand is set to clear the market conditional on the demand of all the investor groups we can observe. This will capture several groups which we know are not included in our data including retail investors, small institutional investors who do not file 13Fs, and foreign institutional investors who also do not file 13Fs. In this section, we aim to understand whether or not this Other group's behavior is related to proxies of retail trading activity.

First, we compare our measure of Other buying and selling to the measure of retail buying and selling in Boehmer et al. (2021). Specifically, leveraging a regulatory requirement for wholesalers, we identify marketable retail buy and sell orders using sub-penny price improvements in the TAQ data. Then, for each stock, each day, we are able to construct a measure of net buying by retail investors. We aggregate this up to the stock-quarter level to match the frequency of our measure of Other demand. Of course, this procedure may produce false positives and false negatives at the individual trade level (i.e., the BJZZ algorithm can classify some retail trades as institutional and classify some institutional trades as retail) (Barber et al., 2022; Battalio et al., 2023). But, as discussed in Laarits and Sammon (2023), aggregated versions of this measure are useful for ranking stocks based on retail trading intensity. We use this procedure to identify retail trades between 2010-2021, since before 2010 the algorithm is relatively less effective at identifying retail trades.

Figure 9 presents a binned scatter plot of our measure of Other demand against the measure of net retail trading activity described above which we constructed using the algorithm in Boehmer et al.

Figure 9: Validation 1: Comparison to BJZZ



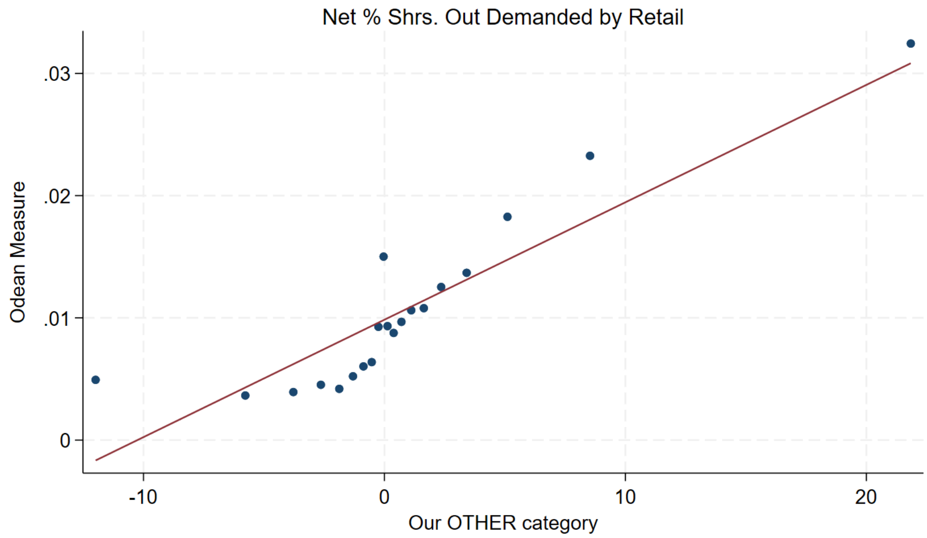
Notes. The x-axis variable is our measure of net Other demand, expressed as a percentage of shares outstanding. The y-axis variable is the net demand by retail investors, expressed as a percentage of shares outstanding, where retail buy and sell orders are identified using the algorithm in Boehmer et al. (2021) (BJZZ). The unit of observation is stock-quarter.

(2021) (hereafter BJZZ). The figure shows that the two measures are strongly positively correlated – suggestive evidence that our measure is indeed capturing retail trading activity. That being said, the scale of the measure constructed using the method in BJZZ is roughly two orders of magnitude smaller than our measure of "Other" trading activity. This could be because BJZZ only captures a fraction of all retail orders (as discussed in Barber et al. (2022) and Battalio et al. (2023), the false negative rate is around 70%), and because our measure – by construction – will pick up net trading by non-retail groups like foreign and small institutions.

Our second validation exercise leverages the retail investor data in Barber and Odean (2000). Specifically, we start with the trade-level data they obtained from a retail brokerage, and aggregate it up to a stock-day measure of net buying by retail investors. This data runs from 1991-1996, and only represents trades at one individual retail brokerage. Therefore, even though the level will likely not match what we find, if this brokerage is representative of the population of retail investors as a whole, we would expected differences in net retail demand to match differences in our measure of "Other" activity. We aggregate this measure of net retail demand to the stock-quarter level to match the frequency of our measure of Other demand.

Figure 10 presents a binscatter plot of our measure of Other demand against the measure of retail activity constructed using trades in Barber and Odean (2000). As with Figure 9, Figure 10 shows that the two measures are strongly positively correlated – further evidence that our measure is indeed capturing retail trading activity. That being said, the scale of the measure constructed

Figure 10: Validation 2: Comparison to Odean Data



Notes. The x-axis variable is our measure of net Other demand, expressed as a percentage of shares outstanding. The y-axis variable is the net demand by retail investors, expressed as a percentage of shares outstanding, where retail buy and sell orders are identified using the transaction-level data in Barber and Odean (2000). The unit of observation is stock-quarter.

using the Barber and Odean (2000) data several orders of magnitude smaller than our measure of retail trading activity. This could be because, as discussed above, their data only includes a single retail brokerage.

A.3 Market Clearing Derivation

From market clearing, we have for a given stock i in a quarter t that

$$\sum_j q_{i,j,t} = 0, \tag{11}$$

and rewriting, we have

$$\sum_j q_{i,j,t} = -q_{i,\text{IDX},t} \tag{12}$$

where j now indexes all groups except Index Funds. We substitute Equation 5 into the expression to yield

$$\sum_j \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t} = -q_{i,\text{IDX},t}. \tag{13}$$

This holds for each stock i in each quarter t. This means we can sum over stocks and quarters, or

$$\sum_i \sum_t \sum_j \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t} = \sum_i \sum_t -q_{i,\text{IDX},t}. \tag{14}$$

We can simplify this to

$$\sum_i \sum_t \sum_j \alpha_j + \sum_j \beta_j \left(\sum_i \sum_t q_{i,\mathrm{IDX},t} \right) = \sum_i \sum_t -q_{i,\mathrm{IDX},t}, \tag{15}$$

since the sum of the error term over time and stocks is zero per group j. This further simplifies to

$$\frac{\sum_i \sum_t \sum_j \alpha_j}{\sum_i \sum_t q_{i,\mathrm{IDX},t}} + \sum_j \beta_j = -1, \tag{16}$$

or

$$\frac{\sum_j \alpha_j}{\overline{q}_{\mathrm{IDX}}} + \sum_j \beta_j = -1, \tag{17}$$

where $\overline{q}_{\mathrm{IDX}}$ is the average Index Fund ownership change over all stocks and quarters. Additionally, given that the alpha represents the estimated quantity bought or sold when Index Fund demand is zero, the market clearing condition also holds in that the sum of the alphas must be zero. That is, the market must clear amongst the other groups when Index Funds do nothing. Thus, we have $\sum_j \alpha_j = 0$, which yields

$$\sum_j \beta_j = -1. \tag{18}$$

B Baseline Empirical Results Appendix

In this appendix, we present supporting analyses for Section 3.

B.1 Fixed Effects

We re-estimate our baseline set of regressions and incorporate a set of fixed effects to address potential common drivers of index fund demand and the demand of other investor groups. Specifically, we implement three distinct specifications.

First, we include year-quarter fixed effects. This accounts for commonalities in flows into index funds within a quarter or aggregate market trends that may affect a group's demand for stocks in general in a particular quarter. This isolates within-quarter variation, and helps address the concern that what drives our results is differences in aggregate effects driving both flows and group asset allocation decisions.

Second, we use industry-by-year-quarter fixed effects to more finely control for commonalities in flows and demand within a quarter. For industry classifications, we use the Fama French 49 industries which are based on four-digit SIC codes (See Ken French's data library for more details). This specification isolates variation within an industry in a given quarter. This specification addresses the impact of industry-specific shocks that might simultaneously influence flows into industry-themed funds and patterns in firm issuance within that industry. For example, if there is a technological shock to computer hardware and semiconductor companies because of a revolution in artificial intelligence, this specification will isolate variation within this set of stocks. That is, we test if more Index Fund demand relative to other stocks in the same industry-quarter is associated with relatively more Firm issuance.

Third, we use year-quarter and firm fixed effects to control for aggregate effects across quarters and patterns at the stock level. One possible explanation of our results is that it is driven by cross-sectional variation between stocks. For example, some stocks tend to regularly issue shares and others tend to regular conduct buybacks, and these patterns are also related to what stocks Index Funds tend to buy or sell. This fixed effects specification asks whether each group's demand is related to variation in Index Fund demand within a company over time.

The betas from these specifications are reported in Table 9. The results are qualitatively unchanged and quantitatively similar to the main estimates reported in Section 3.1. The biggest change is that Firms' and Active Funds' beta are smaller in magnitude with stock and year-quarter fixed effects: Firms' beta is -0.490 (vs. the baseline estimate of -0.642) and Active Funds' beta is 0.144 (vs. 0.193).

Table 9: Beta Estimates with Fixed Effects

	YQ FE			FF49 Industry x YQ FE			Stock and YQ FE		
Investor Group	β_j	$t(\beta_j)$	R^2	β_j	$t(\beta_j)$	R^2	β_j	$t(\beta_j)$	R^2
Active Funds	0.188	11.937	0.022	0.179	11.453	0.052	0.144	9.507	0.066
Other Funds	0.065	8.790	0.100	0.062	8.716	0.131	0.051	7.231	0.142
Pension Funds	0.026	10.362	0.044	0.025	10.158	0.075	0.022	9.036	0.077
Insurance	0.065	13.513	0.036	0.063	13.299	0.067	0.061	12.916	0.060
Financial Institutions	-0.057	-1.198	0.050	-0.085	-1.794	0.083	-0.153	-3.298	0.096
Insiders	-0.089	-12.228	0.008	-0.086	-12.141	0.033	-0.062	-11.633	0.132
Other	-0.267	-5.703	0.039	-0.282	-6.166	0.071	-0.299	-7.063	0.126
Short Sellers	-0.287	-10.534	0.079	-0.283	-10.337	0.112	-0.273	-9.967	0.108
Firms	-0.644	-16.358	0.044	-0.594	-17.069	0.092	-0.490	-16.256	0.212
Total	-1.000			-1.001			-0.999		

Notes. Estimates from a modified version of our baseline regression specification with stock and quarter fixed effects:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\mathrm{IDX},t} + \gamma_i + \psi_t + \varepsilon_{i,j,t}$$

for each investor group j. The unit of observation is security-year-quarter. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

B.2 Horizon Analysis by Sign of Index Fund Demand

In this appendix, we extend the horizon analysis in Section 3.2 by splitting the sample based on stock-quarters with positive and negative Index Fund demand. That is, we condition on the cumulative Index Fund demand at 1, 2, 3, or 4 quarters is either positive or negative. The estimates for positive passive demand shocks are presented in Table 10 and the negative demand shock results are provided in Table 11.

The tables together show that over long horizons, Firms provide nearly all shares for positive Index Fund demand shocks, and our residual Other group buys nearly all shares for negative shocks. Insiders and Short Sellers do help to clear the market for both passive and negative shocks, though their contribution is much smaller than Firms or the Other group. All large demand-side institutions trade in the same direction as Index Funds in the long run, and the effect is much more pronounced for negative passive demand shocks than for positive.

B.3 Value-Weighted Regressions

The baseline regressions give each stock-quarter an equal weight. We re-estimate the set of regressions but on a value-weighted basis, by giving each observation a weight within each quarter proportional to its share of total market capitalization at the end of quarter $t-1$ (i.e., the beginning of quarter t). The baseline regressions give a sense of who typically clears the market for the average stock. The value-weighted regressions give a sense of who typically clears the market

Table 10: Horizon Analysis: Positive Index Fund Demand

	1 Quarter		2 Quarters		3 Quarters		4 Quarters		
Investor Group	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	Obs.
Active Funds	0.192	4.047	0.214	4.650	0.244	5.501	0.259	6.048	103,451
Other Funds	0.111	2.337	0.133	2.969	0.148	3.655	0.159	4.290	103,451
Pension Funds	0.028	6.240	0.031	5.887	0.033	5.754	0.037	5.874	103,451
Insurance	0.077	5.747	0.093	8.352	0.094	12.351	0.099	13.026	103,451
Financial Institutions	-0.106	-0.977	0.078	0.679	0.219	2.065	0.345	3.099	103,451
Insiders	-0.085	-7.016	-0.118	-6.115	-0.136	-5.645	-0.148	-5.414	103,451
Other	-0.054	-0.764	0.100	1.219	0.226	2.273	0.310	2.658	103,451
Short Sellers	-0.306	-5.472	-0.306	-6.565	-0.293	-7.965	-0.293	-9.008	103,451
Firms	-0.855	-16.421	-1.225	-14.028	-1.536	-12.948	-1.768	-10.697	103,451
Total	-0.998		-1.000		-1.001		-1.000		

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t\to t+\ell} = \alpha_j + \beta_j \cdot q_{i,\mathrm{IDX},t\to t+\ell} + \varepsilon_{i,j,t},$$

for each investor group j. $q_{i,j,t\to t+\ell}$ is the quarterly holdings change in stock i for group j from the beginning of year-quarter t to the end of $t+\ell$, where ℓ ranges from 0 to 3, in units of percent ownership of the company. $q_{i,\mathrm{IDX},t\to t+\ell}$ is the cumulative ownership change for Index Funds. The sample conditions on $q_{i,\mathrm{IDX},t\to t+\ell} > 0$ and cumulative ownership change can be computed for four consecutive quarters. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level and we control for autocorrelation up to 6 lags due to partially overlapping data. See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology, and Section 3.2 for more details on the table.

Table 11: Horizon Analysis: Negative Index Fund Demand

	1 Quarter		2 Quarters		3 Quarters		4 Quarters		
Investor Group	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	β_j	$t(\beta_j)$	Obs.
Active Funds	0.142	4.080	0.371	2.960	0.395	2.865	0.397	3.131	37,132
Other Funds	0.018	1.291	0.074	3.205	0.095	4.049	0.098	4.280	37,132
Pension Funds	0.001	0.092	0.039	2.072	0.046	2.316	0.050	2.822	37,132
Insurance	0.042	4.265	0.082	4.437	0.084	4.709	0.087	5.393	37,132
Financial Institutions	-0.378	-4.174	0.509	1.355	0.696	1.621	0.801	2.022	37,132
Insiders	-0.022	-2.172	-0.045	-2.784	-0.082	-4.488	-0.101	-5.495	37,132
Other	-0.865	-7.549	-2.125	-3.649	-2.393	-3.382	-2.543	-3.612	37,132
Short Sellers	-0.112	-2.082	-0.112	-2.375	-0.146	-2.646	-0.174	-2.600	37,132
Firms	0.175	5.139	0.207	3.928	0.304	3.972	0.385	3.766	37,132
Total	-0.999		-1.000		-1.001		-1.000		

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t\to t+\ell} = \alpha_j + \beta_j \cdot q_{i,\mathrm{IDX},t\to t+\ell} + \varepsilon_{i,j,t},$$

for each investor group j. $q_{i,j,t\to t+\ell}$ is the quarterly holdings change in stock i for group j from the beginning of year-quarter t to the end of $t+\ell$, where ℓ ranges from 0 to 3, in units of percent ownership of the company. $q_{i,\mathrm{IDX},t\to t+\ell}$ is the cumulative ownership change for Index Funds. The sample conditions on $q_{i,\mathrm{IDX},t\to t+\ell} < 0$ and cumulative ownership change can be computed for four consecutive quarters. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level and we control for autocorrelation up to 6 lags due to partially overlapping data. See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology, and Section 3.2 for more details on the table.

for the average dollar each quarter. These regressions also highlight the difference in equal- and value-weighted average Firm activity, which we expand on in Appendix D.1.

Table 12 provides the alpha and beta estimates for each group, as well as the average change per group, $\overline{q}_j$. The value-weighted regressions tell a similar story to the equal-weighted regressions above in terms of the sensitivities of each group: Firms and Short Sellers together have a sensitivity of less than -1. In fact, Firms are a bit more sensitive on a value-weighted basis (-0.774 vs. the equal-weighted estimate of -0.694). The most significant difference is the role of Financial Institutions, which has a statistically significant estimate of -0.360, compared to the equal-weighted estimate of -0.054. That is, Financial Institutions are more responsive in dollar terms than percent ownership terms in clearing the market for Index Fund demand. To offset the increased responsiveness of Financial Institutions, Other and Short Sellers have a small decrease in their beta magnitudes. All of the groups with positive equal-weighted betas also have positive betas in dollar terms.

The value-weighted estimates of $\overline{q}_j$ show substantial differences from their equal-weighted counterparts. The group that takes the majority of the other side of Index Funds for the average dollar is not Firms, but rather Financial Institutions and Active Funds. This is consistent with outflows from hedge funds (captured within Financial Institutions) and Active Funds in aggregate. In addition, Firms have a $\overline{q}_j$ that is positive, consistent with significant buyback programs instituted by large public companies.

The results in Table 12 suggest that each of these three groups – Firms, Financial Institutions, and Active Funds – have slightly more nuanced roles in clearing the market for passive demand than suggested by their beta estimates alone. While in value-weighted terms Firms buy back shares on average, they buy back significantly fewer and/or issue more shares as Index Funds increase their demand. Further, the average dollar demand by Financial Institutions offsets Index Fund demand, and they continue to supply additional dollars as Index Funds demand more, though at about half the rate of Firms. Finally, the average dollar demand for Active Funds also offsets Index Fund demand, but they respond to greater passive demand by selling less/buying more of the same stocks.

The equal- and value-weighted estimates collectively point to a single overarching story. Firms are *by far* the most responsive to changes in Index Fund demand at both the stock and dollar level – when Index Funds buy more, Firms provide more shares. In addition, Short Sellers and Insiders also provide more shares as Index Funds demand more shares. All 13F groups besides Financial Institutions – Active Funds, Other Funds, Insurance, and Pension Funds – increase their demand for shares when Index Funds demand more shares. These statements all speak to the *relative* responsiveness of these groups.

Table 12: Regression Estimates: Value-Weighted Regressions

Investor Group	β_j	$t(\beta_j)$	α_j	$t(\alpha_j)$	Obs.	R^2	$\bar{q}_j$
Active Funds	0.233	4.089	-0.142	-7.424	172,807	0.006	-0.142
Other Funds	0.188	2.516	0.054	2.605	172,807	0.026	0.054
Pension Funds	0.032	5.646	-0.023	-2.419	172,807	0.005	-0.023
Insurance	0.090	3.910	-0.058	-3.597	172,807	0.005	-0.058
Financial Institutions	-0.382	-3.103	-0.048	-0.423	172,807	0.005	-0.048
Insiders	-0.081	-6.470	-0.034	-3.116	172,807	0.004	-0.034
Other	-0.182	-1.893	-0.086	-0.760	172,807	0.001	-0.086
Short Sellers	-0.162	-6.990	0.022	1.055	172,807	0.006	0.022
Firms	-0.736	-15.000	0.315	7.080	172,807	0.038	0.315
Total	-1.000		-0.000				-0.000

Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j with each observation given a weight proportional to stock i's share of total stock market capitalization in quarter $t-1$. The unit of observation is security-year-quarter. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

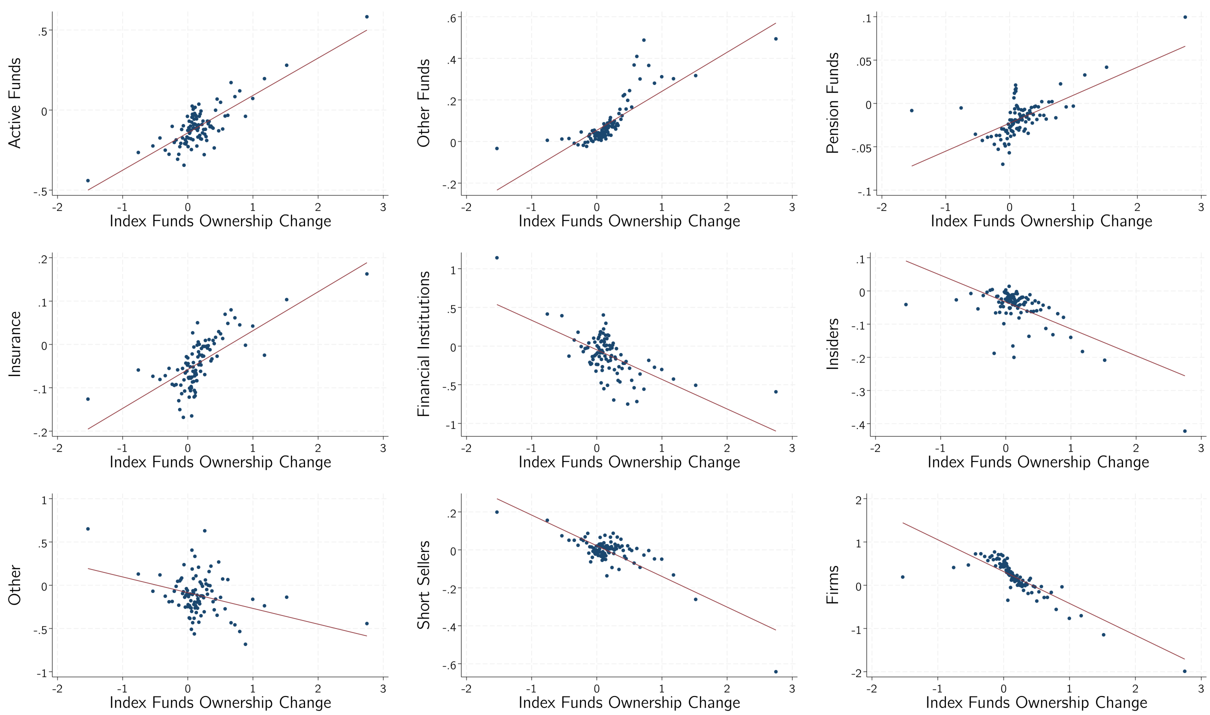
Value-Weighted Binscatter Plots We provide binscatter plots that correspond to the value-weighted regressions in Table 12. Figure 11 presents the data in a value-weighted binscatter plot. We divide the data into 100 bins, and all observations in each bin are weighted by the firm's share of total market capitalization at the end of the previous quarter. The plots show very similar patterns to the equally-weighted plots in Section 3.1.2. The biggest change is with Financial Institutions, which look to play a more definitive role in clearing the market for passive for all but the largest Index Fund ownership increases. The other significant change is with the Other group, which looks much smaller and noisier, consistent with both retail investors focusing on small-cap stocks and a greater chance of data errors in small-cap stocks.

B.4 Sample Selection Robustness

Sample Selection We show that our baseline findings are even stronger when examining sub-samples of the data. We report regression estimates from 2009-2021 and 2015-2021 in Table 13.

Treatment of Outliers Section 2.2 outlines our reasons for trimming outliers for the regressions reported in Section 3.1. We repeat our main analyses by using the raw data and by Winsorizing outliers at the 0.5 and 99.5 percentiles. We report the regression estimates with these alternative approaches for handling outliers in Table14.

Figure 11: Value-Weighted Binscatter by Group



Notes. Each panel presents a value-weighted binscatter of net demand by each investor group – $q_{i,j,t}$ – against net demand by Index Funds – $q_{i,\mathrm{IDX},t}$. The unit of observation is security-year-quarter.

Table 13: Regression Estimates: 2009-2021 and 2015-2021

	2009-2021				2015-2021			
Investor Group	β_j	$t(\beta_j)$	Obs.	R^2	β_j	$t(\beta_j)$	Obs.	R^2
Active Funds	0.203	6.932	137,431	0.011	0.179	5.198	80,729	0.013
Other Funds	0.091	3.172	137,431	0.015	0.105	2.890	80,729	0.022
Pension Funds	0.019	6.078	137,431	0.004	0.021	5.682	80,729	0.009
Insurance	0.070	8.816	137,431	0.015	0.072	7.672	80,729	0.027
Financial Institutions	-0.054	-0.803	137,431	0.000	0.053	0.704	80,729	0.000
Insiders	-0.101	-11.170	137,431	0.006	-0.093	-10.669	80,729	0.007
Other	-0.272	-4.765	137,431	0.004	-0.264	-3.657	80,729	0.005
Short Sellers	-0.263	-9.198	137,431	0.023	-0.301	-9.488	80,729	0.038
Firms	-0.694	-15.837	137,431	0.037	-0.771	-12.621	80,729	0.044
Total	-1.001				-0.999			

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t},$$

for each investor group j for two alternative samples: 2009-2021 and 2015-2021. $q_{i,j,t}$ is the quarterly holdings change in stock i for group j in year-quarter t in units of percent ownership of the company. $q_{i,\text{IDX},t}$ is the ownership change for Index Funds. T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level. See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology, and Section 3.1 for more details on the table.

Table 14: Beta Estimates: 2002-2021, Raw and Winsorized Data

	Raw Data				Winsorized Data			
Investor Group	β_j	$t(\beta_j)$	Obs.	R^2	β_j	$t(\beta_j)$	Obs.	R^2
Active Funds	0.516	4.965	185,799	0.068	0.193	7.015	172,807	0.007
Other Funds	0.132	6.669	185,799	0.034	0.086	3.148	172,807	0.012
Pension Funds	0.052	3.724	185,799	0.012	0.022	7.423	172,807	0.004
Insurance	0.104	7.616	185,799	0.023	0.065	7.894	172,807	0.008
Financial Institutions	0.632	2.170	185,799	0.021	-0.152	-2.265	172,807	0.001
Insiders	-0.114	-6.481	185,799	0.002	-0.084	-10.920	172,807	0.005
Other	-1.325	-2.605	185,799	0.055	-0.250	-4.674	172,807	0.003
Short Sellers	-0.221	-6.066	185,799	0.017	-0.238	-6.433	172,807	0.015
Firms	-0.775	-7.638	185,799	0.035	-0.642	-16.196	172,807	0.032
Total	-0.999				-1.000			

Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. The unit of observation is security-year-quarter. Unlike in Table 1, the data is not trimmed for each group at the 0.5 and 99.5 percentiles. Instead, we include the raw (untrimmed, non-Winsorized) data in the first specification and the Winsorized data in the second specification. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

B.5 Data Errors

One concern arises from the nature of the data. As described in Section 2 and documented in detail in Sammon and Shim (2023), the S12 data is littered with many types of errors, some of which involve staleness in reported holdings. We also find evidence of data errors in the Thomson 13F data. We address two types of data errors: (1) general data errors where a group appears to increase or decrease its ownership of a stock but does not in reality, and (2) stale data.

General data errors result in an inability to clear the market amongst the groups in our sample, and force the residual Other group to take a position that mechanically clears the market. This will have the effect of attenuating the beta estimates of each of the non-residual groups, and push the beta estimate of the Other group toward -1. In this sense, the data errors have the same effect as the well-known attenuation bias due to measurement error. This suggests that our estimates for the non-residual groups in Table 1 are an underestimate.

B.5.1 Minimal Residual Demand

All of our measures of net demand come directly from the data except our residual Other category, which is necessary to ensure market clearing holds in our data. The Other category by construction makes a position change that all other investors that are not included in our data must have done in order for the market to clear. There are a few ways to look at this. One is that our Other category is actually picking up some combination of foreign investors, small institutions, and retail traders (in Appendix A.2.3, we provide evidence that our Other category is related to measures of retail trading activity). An alternative interpretation is that this Other category represents an aggregation of data errors for the investors we do have in our data. This can be due to issues with mistiming (e.g., reporting delays, stale data) or just pure data errors, and are all collected in this residual group. Last, it could be that there is some kind of dark matter that clears the market, but we do not know who they are.

As a check, we examine only the observations where the market clears or nearly clears amongst the investor groups we can directly measure in our data. That is, we filter out all observations where our residual group are required to trade more than 0.50% of shares outstanding to make the market clear. Table 15 presents the estimates.

While this exercise omits a significant fraction of the data, the general message is consistent with the baseline results – Firms and Short Sellers collectively account for a significant fraction of the shares demanded by passive. The magnitude is a bit lower than the baseline estimates: Firms have a beta of -0.404 (vs. -0.642 in the baseline) and Short Sellers have a beta of -0.17 (vs. -0.238). Financial Institutions play a much larger role in clearing the market in this sample, with a beta estimate of -0.514 (vs. -0.152). The changes in point estimates are likely driven by observations

Table 15: Regression Estimates: Sample with Low Other Group Activity

Investor Group	β_j	$t(\beta_j)$	α_j	$t(\alpha_j)$	Obs.	R^2	$\bar{q}_j$
Active Funds	0.028	0.996	-0.062	-3.121	36,785	0.000	-0.055
Other Funds	0.059	3.327	0.055	3.599	36,785	0.005	0.070
Pension Funds	0.013	4.126	-0.008	-1.624	36,785	0.001	-0.005
Insurance	0.041	7.334	-0.026	-2.379	36,785	0.003	-0.016
Financial Institutions	-0.514	-9.750	-0.029	-0.669	36,785	0.026	-0.155
Insiders	-0.046	-6.410	0.011	1.969	36,785	0.004	-0.000
Other	-0.008	-2.791	-0.012	-4.741	36,785	0.000	-0.014
Short Sellers	-0.170	-4.690	0.083	2.412	36,785	0.009	0.041
Firms	-0.404	-12.503	-0.012	-0.622	36,785	0.035	-0.111
Total	-1.001		-0.000				-0.246

Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. The unit of observation is security-year-quarter. Run on the subsample of observations where the absolute value of $q_{i,j,t}$ is less than 0.50%. t-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

with large positive or negative changes in Index Fund ownership, which we discuss and explore more in Section 3.1.3.

B.5.2 Stale Data

Stale data may impact the results in an a way that is different than more general data errors. Imagine a scenario where, in reality, Index Funds buy a stock in period t and Active Funds sell to them, but Active Funds' sales are erroneously not recorded in the data and stale holdings from the previous quarter are recorded instead. In order to clear the market, the residual Other group will then be responsible for clearing the market in period t. In addition, the Active Fund sale, which is now recorded with a delay in $t+1$, will be cleared by the Other group's buying. That is, the Other group will look as if it acts as an intermediary between groups over quarters.

To quantify how problematic stale data is, we test the degree to which passive changes in quarter t are related to other groups' position changes in the same stock but in quarter $t+1$. That is, we estimate

$$q_{i,j,t+1} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t+1} \tag{19}$$

for each group in our sample. The notable difference is the left-hand side variable, $q_{i,j,t+1}$, is in quarter $t+1$, not t.

If the sign of the beta estimate for the Other group flips sign from t (the baseline regressions) to $t+1$, that would be consistent with, though not definitive proof of, the data being stale. We report

Table 16: Beta Estimates with Future Group Changes

Investor Group	β_j	$t(\beta_j)$	α_j	$t(\alpha_j)$	Obs.	R^2	$\bar{q}_j$
Active Funds	0.065	5.731	-0.050	-1.845	162,315	0.001	-0.027
Other Funds	0.032	6.267	0.069	2.769	162,315	0.002	0.080
Pension Funds	0.008	3.696	-0.010	-1.704	162,315	0.001	-0.007
Insurance	0.019	5.162	-0.019	-1.432	162,315	0.001	-0.012
Financial Institutions	0.025	0.662	0.050	0.586	162,315	0.000	0.059
Insiders	-0.047	-9.559	-0.034	-4.757	162,315	0.002	-0.050
Other	0.097	2.681	0.105	1.399	162,315	0.001	0.139
Short Sellers	-0.081	-3.313	0.012	0.256	162,315	0.002	-0.016
Firms	-0.260	-13.778	-0.368	-9.386	162,315	0.006	-0.458
Total	-0.142		-0.245				-0.294

Notes. Estimates a modified version of our baseline regression specification where we compare investors' net demand in quarter $t+1$ against passive demand in quarter t:

$$q_{i,j,t+1} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. The unit of observation is security-year-quarter. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

these beta estimates in Table 16.

The table shows a beta estimate for the residual group of 0.097. That is, Index Fund changes at t are negatively related to the residual group's position change in t but positively related in $t+1$. This is consistent with at least some portion of the data being stale. In addition, the groups most likely to have stale data appear are those that have the opposite of Other in $t+1$, which, again, is Firms.

This robustness test also yields more insight into the role of Firms and Short Sellers. Table 16 shows that these groups adjust positions in $t+1$ in the opposite direction of Index Fund changes in t. That is, if Index Funds buy a stock in quarter t, Firms and Short Sellers tend to sell in both quarters t and $t+1$. The estimates for Firms and Short Sellers, respectively, are -0.26 and -0.081. While the betas for future changes are about a third of the magnitude of betas for contemporaneous changes, they are the most economically significant coefficients for quarter $t+1$.

B.6 By Stock Characteristics

B.6.1 By Industry

One reason why Firms issue shares is for employee compensation. Employees may receive shares, then sell them in the market, which could end up in the hands of Index Funds. Note, however, that this does not include current executives, which are captured by our Insiders group. This type of compensation appears to be more prevalent with technology firms and young firms.

In this appendix, we examine whether the tendency for some industries to issue more stock (perhaps via compensation) are more responsive to Index Fund demand. This may also capture general tendencies in primary market activity by industry, including how responsive primary market activity in an industry (buybacks and issuance) might be to secondary market activity (Ma, 2019).

Table 17 presents the beta estimates in Panel (A) and the average position change in Panel (B) for each of the Fama-French 10 industries.[30] The table shows that beta estimates vary the most for Firms and Financial Institutions, and they tend to substitute for one another, just as in non-linear analysis in Sections 3.1.2 and 3.1.3, and the over-time analysis in Appendix B.7. Firms do indeed tend to be more responsive to Index Fund changes in industries known for more stock compensation (high-technology and healthcare), but also are active in other more surprising industries (energy and "other", which contains the financial sector). Regardless, Firms appear to at least be somewhat responsive to Index Funds for *every* industry. On the other hand, Financial Institutions have estimates close to zero or positive for several industries. The other seven groups have largely similar estimates, regardless of industry.

Panel (B) also reports the average position change by group. This shows that Firms and Insiders have the most consistently negative estimates across industries. On the other hand, Financial Institutions have just as many negative industry averages as positive. Taken together, Panels (A) and (B) suggest that Firms most steadily provide shares to Index Funds and are the most responsive in issuing more shares with greater Index Fund demand, regardless of industry. There is also heterogeneity across industries – energy, high tech, healthcare have both the most issuance on average and are the most responsive in issuing as Index Funds demand more.

B.7 Beta Estimates over Time

Given the time trend in passive ownership, significant events that likely adjusted portfolio allocations like COVID-19, and improvements in data quality, we further study how our series of beta estimates vary over time. To check for time trends in who is on the other side of passive trades, we estimate the baseline regressions for each group, but do so separately for each quarter in our data. That is, we estimate a series of cross-sectional regressions, which recover a beta estimate per non-passive group per quarter.

Figure 12 visually presents the beta estimates for each group using an 8-quarter moving average to smooth out estimation errors and get a better sense of the general patterns.

There are two significant trends, each going in the opposite direction. Firms have beta estimates that are growing in absolute value, going from around -0.5 at the beginning of the sample and steadily declining starting from around 2008 to end the sample with estimates of nearly -1. Over

[30] See Ken French's data library for details on industry classifications.

Table 17: Estimates by Industry

Panel A: Betas

Investor Group	Nondurables	Durables	Manuf.	Energy	High Tech	Telecom	Shops	Health	Utilities	Other
Active Funds	0.091	0.103	0.080	0.239	0.153	0.129	0.175	0.227	0.051	0.239
Other Funds	0.063	0.071	0.067	0.076	0.089	0.052	0.072	0.080	0.090	0.097
Pension Funds	0.022	0.018	0.011	0.019	0.022	0.021	0.025	0.024	0.007	0.024
Insurance	0.045	0.096	0.057	0.066	0.057	0.043	0.063	0.074	0.064	0.069
Fin. Insts. Ex. Funds	-0.428	-0.479	-0.470	-0.022	-0.280	-0.400	-0.490	-0.005	-0.373	0.027
Insiders	-0.044	-0.084	-0.052	-0.051	-0.071	-0.074	-0.099	-0.043	-0.054	-0.111
Other	-0.289	-0.300	-0.195	-0.392	-0.247	-0.165	-0.297	-0.353	-0.227	-0.229
Short Sellers	-0.198	-0.191	-0.139	-0.288	-0.184	-0.166	-0.181	-0.308	-0.125	-0.278
Firms	-0.262	-0.233	-0.360	-0.647	-0.539	-0.439	-0.267	-0.697	-0.432	-0.838
Total	-1.000	-0.999	-1.001	-1.000	-1.000	-0.999	-0.999	-1.001	-0.999	-1.000

Panel B: $\bar{q}_j$

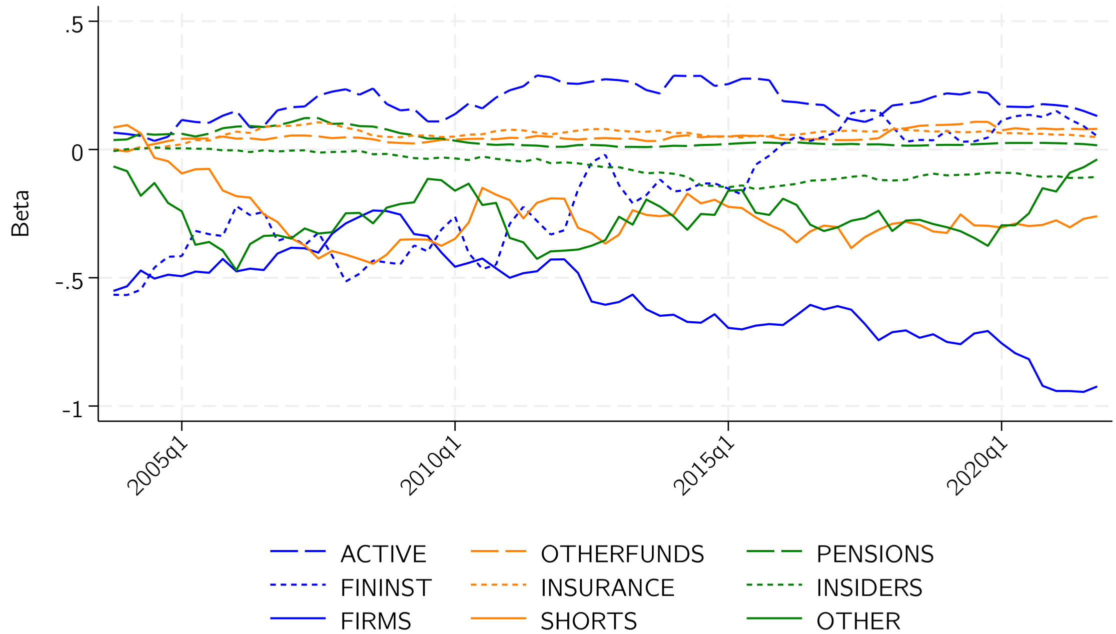
Investor Group	Nondurables	Durables	Manuf.	Energy	High Tech	Telecom	Shops	Health	Utilities	Other
Active Funds	0.010	-0.062	-0.024	0.013	-0.020	-0.098	-0.126	0.069	0.072	0.063
Other Funds	0.071	0.067	0.079	0.067	0.097	0.041	0.058	0.091	0.101	0.101
Pension Funds	-0.013	-0.009	-0.009	0.012	-0.000	0.002	-0.015	0.005	-0.001	0.006
Insurance	-0.033	-0.018	-0.015	-0.013	-0.010	-0.027	-0.027	0.002	0.003	0.005
Fin. Insts. Ex. Funds	-0.060	-0.120	-0.089	0.094	0.133	0.032	-0.162	0.259	0.177	0.141
Insiders	-0.050	-0.013	-0.019	-0.067	-0.047	-0.047	-0.081	-0.014	-0.015	-0.094
Other	0.040	0.000	-0.019	0.509	0.076	0.195	0.050	0.382	-0.052	0.200
Short Sellers	-0.033	0.002	0.006	-0.139	-0.008	-0.019	-0.018	-0.071	-0.030	-0.062
Firms	-0.181	-0.101	-0.183	-0.879	-0.531	-0.348	0.073	-1.066	-0.582	-0.738
Total	-0.249	-0.254	-0.273	-0.403	-0.312	-0.270	-0.249	-0.342	-0.326	-0.377

Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\mathrm{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. The regression is estimated separately, in each column only including firms which are a member of each of the listed industries. The unit of observation is security-year-quarter. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

Figure 12: Betas Estimates over Time



Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\mathrm{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. This regression is run separately each quarter, and the lines represent an 8-quarter moving average of the betas estimated each quarter.

the same period, Financial Institutions are steadily increasing, from an estimate of around -0.5 at the beginning of the sample to around 0.1 at the end.

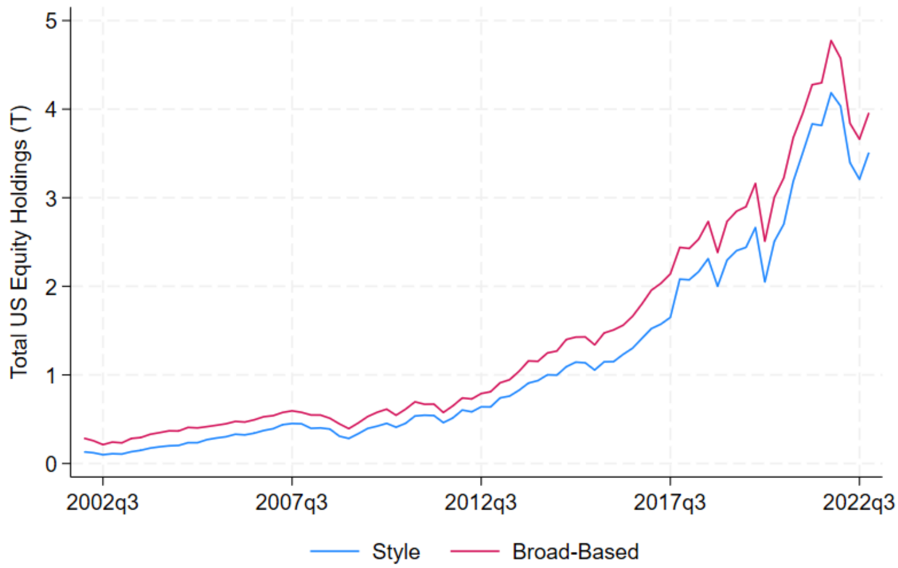
These patterns suggest that the void left in responsiveness by Financial Institutions, who by the end of the sample are, on average, buying and selling more when Index Funds buy or sell more, are offset by Firms who are becoming increasingly more responsive.

Our residual Other group's beta also appears to be trending somewhat toward zero for most of the sample, with an estimate around -0.4 within the first few years of our sample ending up around -0.1 at the very end of out sample. This is consistent with the Other group offsetting some data errors, but data quality improving over time. This could also relate to retail investors increasingly trading in a way that is orthogonal to Index Fund demand.

Many of the smoothed estimates are relatively stable over time. For example, Active Funds, Short Sellers, Insiders, and Insurance all have beta estimates that look roughly unchanged over the entire sample period.

These facts collectively support two non-mutually exclusive themes. First, as passive has continued to grow over time, Firms have continued to take a larger and larger role in making shares available

Figure 13: Total Assets Managed by Broad-Based Index Funds and Style Index Funds



Notes. Total dollars of US equity holdings by Style and Broad-Based passive funds.

as Index Funds demand more shares, while other institutions and mutual funds have had little to no change in their responsiveness. Second, as the quality of our data has improved, one of our main conclusions, that share suppliers (Firms and Short Sellers) are more responsive in providing shares when Index Funds demand more, appears to gain more support.

B.8 Broad-Based vs. Style Funds

The largest index funds by AUM are broad-based funds that track a large swath of stocks across a range of industries and characteristics like Vanguard's Total Market Fund, VTI. But there has also been significant growth in what we call "style" index funds, which track indices based on specific industries and factors, ranging from a "value" version of the S&P 500 (IVE) to a fund that tracks the pharmaceutical industry (e.g., PPH) or targets stocks with high free cash flow yield (e.g., COWZ). Figure 13 shows that these style index funds are collectively large – with similar total AUM to the broad-based funds – although they are individually much smaller, as there more than 20 times as many style funds as there are broad-based funds.

Table 18 presents the regression estimates separately with demand only from broad-based Index Funds as the focal group and again with style-based Index Funds. In each set of regressions, we also include the omitted Index Fund group as a separate investor group j. The estimates show that Firms have the most negative beta regardless of whether we focus on broad-based or style Index Fund demand. Firms are much more responsive to broad-based than style Index Funds, partially because there is "more to clear" in the sense that style funds tend to mimic the demand

Table 18: Beta Estimates by Index Fund Type

	Broad-Based Index Funds				Style Index Funds			
Investor Group	β_j	$t(\beta_j)$	α_j	$t(\alpha_j)$	β_j	$t(\beta_j)$	α_j	$t(\alpha_j)$
Active Funds	0.364	6.051	-0.039	-1.493	0.241	5.106	-0.032	-1.430
Other Funds	0.139	3.673	0.067	3.137	0.122	2.316	0.064	3.798
Pension Funds	0.042	4.432	-0.006	-0.969	0.025	6.031	-0.005	-0.851
Insurance	0.113	5.863	-0.023	-1.805	0.084	5.693	-0.023	-1.825
Financial Institutions	0.017	0.089	0.064	0.742	-0.305	-3.214	0.122	1.407
Insiders	-0.197	-9.534	-0.033	-4.479	-0.104	-8.434	-0.041	-5.671
Other	-0.201	-1.505	0.147	1.913	-0.249	-3.368	0.165	2.176
Short Sellers	-0.242	-1.466	0.002	0.051	-0.309	-9.470	0.025	0.518
Firms	-1.532	-11.956	-0.292	-7.521	-0.704	-15.208	-0.377	-10.523
Index Funds (Broad)					0.199	14.063	0.103	8.917
Index Funds (Style)	0.498	15.340	0.112	8.564				
Total	-0.999		-0.001		-0.999		0.000	

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t},$$

for each investor group j. We separately estimate the regression where $q_{i,\text{IDX},t}$ is the ownership change for broad-based Index Funds (e.g., S&P 500) and style Index Funds (e.g., value funds and industry funds). $q_{i,j,t}$ is the quarterly holdings change in stock i for group j in year-quarter t in units of percent ownership of the company. When testing broad-based Index Funds, we include style Index Funds as another group j (and vice versa). T-statistics are computed from standard errors double clustered at the stock and time (year-quarter) level. See Section 2.2 for more details on the investor groups, Section 2.3 for the empirical methodology.

of broad-based funds. That is, when broad-based funds buy, style funds tend to buy more of the same stock, and Firms must accommodate not only the broad-based fund demand but also the style fund demand that typically accompanies it.

B.9 Index Effects

There is a long literature that studies index additions and deletions as a source of inelastic demand shocks that originates from Shleifer (1986) and Harris and Gurel (1986). In that spirit, we test whether there are differences in who trades with passive when stocks have switched indices (i.e., "switchers") or have not had any change in any major index it belongs to (i.e., "stayers").

Collectively, the tests point to a story where intermediaries can facilitate trading between Index Funds and other institutions if there is a clear signal or event where passive will demand shares. This is similar to the role intermediation might play in facilitating the trades required from index changes, as documented in Chinco and Sammon (2023). Without this signal for intermediaries, the supply side plays the largest role in clearing the market.

B.9.1 Index Switchers vs. Stayers

We examine stocks that did or did not switch membership in major indices. This section is closely related to contemporaneous work by Tamburelli (2024). While their analysis uses S&P 500 additions as an exogenous shock to passive demand, we simply separately study index switchers vs. stayers as part of our market clearing exercise. Each quarter, we define a stock as an index switcher ("switcher") if it moved into or moved between any of the major indices (e.g, S&P 500, 400, 600 and the Russell 1000 and 2000; see Section A.1 for the full list). Otherwise, the stock is categorized as a "stayer." We split the sample based on this designation.[31] Table 19 presents the estimates for each subsample.

The index stayers tell a largely similar story to the overarching theme of the paper: Firms account for most of the other side of passive (both on average and in terms of their responsiveness), with Short Sellers and Insiders also consistently contributing to clearing the market for Index Funds.

Market clearing is quite different for index switchers. Most notably, Firms play a much larger *average* role: $\overline{q}_j$ for Firms is -1.082pp, nearly all of the 1.102pp average Index Fund demand for index switchers. However, Firms are much less *responsive*, with a beta estimate of -0.201 (as opposed to -0.763 for stayers).[32] This compliments the results in Tamburelli (2024), which shows that firms accommodate inelastic demand from low tracking-error funds around S&P 500 index inclusion events. It is also consistent with the anecdotal high profile cases of equity issuance around S&P 500 index inclusions by, e.g., Facebook (Meta) and Tesla.

In order for the market to clear, which groups take a larger role on the other side of increased passive demand? The biggest differences come from Financial Institutions, Active Funds, and Other Funds. In fact, Active Funds and Other Funds appear to be breaking a persistent pattern we have seen throughout the paper: instead of trading in the same direction as Index Funds, they actually accommodate increased Index Fund ownership changes.

This points to a story where a salient event, like a stock switching indices, may help facilitate the transfer of shares amongst funds and institutional investors. Financial intermediaries may be able to use the attention these stocks garner to get demand-side institutions to adjust portfolio allocations to clear the market (Greenwood and Sammon, 2022). Firms also provide an important role in market clearing by providing a significant fraction of the shares on average, but are much less responsive to deviations from the average Index Fund demand than in the index stayers sample (and, for that matter, in most other subsamples).

[31] Relative to the size of all stocks held by all indices in our data, switching is rare. We still think that this is an important exercise given the salience of index switching and the attention it receives from investors and academics.

[32] One reason for this difference could be large differences within switchers based on whether a stock is coming from outside of a major index to inside a major index (and vice versa) relative to a stock that is switching indices within the same index family. For the former, many of the shares must come from outside of Index Funds. For the latter, many of the shares come from within the Index Fund group see, e.g., Greenwood and Sammon (2022).

Table 19: Beta Estimates: Index Switchers vs. Stayers

	Index Switchers						Index Stayers					
Investor Group	β_j	$t(\beta_j)$	α_j	Obs.	R^2	$\overline{q}_j$	β_j	$t(\beta_j)$	α_j	Obs.	R^2	$\overline{q}_j$
Active Funds	-0.024	-0.841	-0.054	1,424	0.001	-0.080	0.235	7.164	-0.073	134,394	0.013	0.002
Other Funds	-0.033	-2.083	0.255	1,424	0.008	0.219	0.104	3.060	0.065	134,394	0.018	0.098
Pension Funds	0.013	2.010	0.047	1,424	0.008	0.061	0.017	4.795	-0.005	134,394	0.003	0.000
Insurance	0.089	8.529	0.017	1,424	0.094	0.115	0.064	6.775	-0.024	134,394	0.011	-0.004
Financial Institutions	-0.147	-1.897	0.728	1,424	0.008	0.566	-0.068	-0.926	0.103	134,394	0.000	0.081
Insiders	0.001	0.123	-0.108	1,424	0.000	-0.107	-0.114	-10.580	-0.035	134,394	0.007	-0.071
Other	-0.328	-4.413	0.437	1,424	0.030	0.075	-0.249	-3.759	0.341	134,394	0.003	0.262
Short Sellers	-0.370	-7.681	-0.461	1,424	0.146	-0.869	-0.225	-8.835	0.042	134,394	0.015	-0.030
Firms	-0.201	-2.609	-0.860	1,424	0.015	-1.082	-0.763	-16.627	-0.414	134,394	0.039	-0.657
Total	-1.000		0.001			-1.102	-0.999		-0.000			-0.319

Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. The sample is split into index switchers – defined as those that are added to, dropped from or switch between the Russell 1000, Russel 2000, S&P 500, S&P 400, S&P 600, Nasdaq 100 or the CRSP Total Market. The unit of observation is security-year-quarter. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

We can report that that the lack of Firm responsiveness for switchers is largely temporary – over the course of a year, Firms are the most sensitive in providing shares to Index Funds with a beta estimate similar in magnitude to our baseline regressions. In addition, the negative beta estimates for Active Funds and Financial Institutions observed in the quarterly regressions flip to positive at longer horizons, reinforcing the role that these groups may play in short-term intermediation, especially when a salient event, like switching an index, draws attention to possible uninformed trading by indexers.

B.9.2 Index Migrations and Direct Additions/Deletions

We further study index switchers in light of how different market clearing looks relative to the baseline results. In addition, better understanding these stocks helps provide greater context to index switching events, which are the focus of a long literature. We separate index switchers into several categories. First, we examine direct additions, which are stocks that moved from outside of an index fund family to within it. For example, a stock that was added to the S&P 500 that was not previously held by the S&P 500, 400, or 600 would be a direct addition. Similarly, we also separately examine direct deletions.

Second, we examine stocks that migrated from one index to another related index (e.g., Russell 1000 to 2000). These events typically have a much smaller change in overall (net) Index Fund ownership because many of the shares that need to be sold or bought are exchanged between Index Funds. That is, in these cases, the market clears for a non-trivial fraction (and, in many cases, the majority) of shares within the Index Fund group. We separately study migrations that led to net buying or net selling by Index Funds. The alpha, beta and $\overline{q}_j$ estimates for our series of regressions for each subsample are presented in Table 20. The table also shows the number of observations for each sample to get a sense of how rare these events are, and also presents the average ownership change for Index Funds and for all institutions (in percentage points) to get a sense of magnitudes for each type of event.

Panel A of Table 20 focuses on direct additions and deletions – showing that who clears the market in each of these cases is quite different. As in our baseline results, for additions, Firms and Short Sellers tend to be the most responsive in supplying shares (this time with Short Sellers supplying relatively *more* shares for each additional unit of Index Fund demand than Firms), with Financial Institutions also playing an important role. For deletions, Short Sellers are about as active in clearing the market (by reducing their short positions) and Firms are not responsive at all. Instead, Other is the most responsive. This is consistent with these stocks leaving the investable universe and finding buyers in retail investors, as well as small institutional investors who may have fewer mandates preventing them from buying such stocks.

However, the betas alone undersell the role of Firms and Short Sellers in accommodating passive demand around index additions. The alphas for these groups are large, and as a result, the associated $\overline{q}_j$s are large as well. Further, the alpha for Financial Institutions is large and positive, evidence that despite a negative beta, this group is predicted to be a net buyer around the typical index addition event, in a way that is not correlated to the size of the demand shock by Index Funds. Similarly, for deletions, we see that the alpha for Other is large, further evidence that foreign institutions, small institutions and retail investors are needed to clear the market when a firm leaves the investable universe and is unlikely to be held by most U.S. institutions.

Panel B of Table 20 focuses on migrations. In the cases of migrations where Index Funds are net buyers of shares (e.g., firms switching from the Russell 1000 to the Russell 2000), Financial Institutions are the most responsive, with a beta of -0.51. Short Sellers and Active are the next most responsive groups, with betas of -0.30 and -0.20, respectively. While Firms have a positive beta, they have a large negative alpha, and therefore a moderately negative $\overline{q}_j$, suggesting that they do play an important role in clearing passive demand around migration events with net passive buying, however more through what they tend to do on average, rather than how they respond to the amount of passive demand.

When Index Funds are net sellers of shares around migrations (e.g., the case of firms migrating from the Russell 2000 to the Russell 1000), Financial Institutions and Firms are the most responsive. That being said, around such events, the alpha for Firms is large and negative, leading to a negative $\overline{q}_j$ for this group. In fact, the $\overline{q}_j$s suggest that our Other group, as well as Financial Institutions and non-passive mutual funds, tend to be the most important groups for clearing the market on average in this subsample.

Table 20: Beta Estimates: Index Additions, Deletions, and Migrations

	Panel A: Direct Adds/Drops					
	Betas		Alphas		$\overline{q}_j$	
Investor Group	Additions	Deletions	Additions	Deletions	Additions	Deletions
Active Funds	0.039	0.290	0.108	-0.307	0.200	-0.552
Other Funds	0.075	-0.059	0.036	0.037	0.213	0.087
Pension Funds	0.035	0.040	0.080	-0.044	0.162	-0.078
Insurance	0.074	0.087	0.144	-0.187	0.319	-0.261
Financial Institutions	-0.201	-0.098	1.552	-0.792	1.079	-0.709
Insiders	-0.044	-0.106	-0.056	-0.225	-0.159	-0.135
Other	-0.385	-0.980	0.307	2.046	-0.601	2.876
Short Sellers	-0.374	-0.215	-0.706	-0.480	-1.587	-0.298
Firms	-0.220	0.040	-1.465	-0.051	-1.984	-0.084
Total	-1.000	-1.000	0.000	0.000	-2.359	0.847
# Obs.					1,739	103
Avg. Index Fund Ownership Chg. (pp)					2.359	-0.847
Avg. Institutions Ownership Chg. (pp)					4.331	-2.359

	Panel B: Migrations					
	Betas		Alphas		$\overline{q}_j$	
Investor Group	Net Buying	Net Selling	Net Buying	Net Selling	Net Buying	Net Selling
Active Funds	-0.204	0.085	0.167	0.286	-0.261	0.143
Other Funds	-0.042	-0.075	0.098	0.312	0.010	0.438
Pension Funds	-0.005	-0.027	-0.100	0.048	-0.110	0.093
Insurance	0.081	0.028	-0.012	-0.065	0.158	-0.112
Financial Institutions	-0.507	-0.354	1.222	0.190	0.160	0.784
Insiders	0.015	-0.015	-0.155	-0.193	-0.123	-0.168
Other	-0.202	-0.307	0.005	0.555	-0.417	1.071
Short Sellers	-0.297	-0.033	-0.363	0.097	-0.986	0.153
Firms	0.162	-0.301	-0.863	-1.231	-0.524	-0.726
Total	-1.000	-1.000	0.000	0.000	-2.094	1.678
# Obs.					503	515
Avg. Index Fund Ownership Chg. (pp)					2.094	-1.678
Avg. Institutions Ownership Chg. (pp)					0.846	0.846

Notes. Estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j estimated on each subsample. In Panel A, the sample is split into direct additions and deletions. Direct additions are defined as securities that are added to the S&P 500, S&P 400, S&P 600 from outside the S&P 1500 universe, securities added to the Russell 1000 or 2000 from outside the Russell 3000 universe and securities which are added to the Nasdaq 100 or CRSP Total Market Indices. Direct deletions are defined similarly, as firms that leave these indices to outside of their respective index universes. In Panel B, the sample includes only migrations, and is split based on whether there is net buying or net selling by passive funds. An example of a migration typically associated with net buying is a migration from the Russell 1000 to the Russell 2000, while an example of a migration typically associated with net selling is a migration from the Russell 2000 to the Russell 1000. The unit of observation is security-year-quarter.

C Identification and Mechanism Appendix

C.1 Instrumental Variables and Market Clearing

In the body of the paper, we focused on Firms' demand as the key outcome variable of interest in our IV regression. In Table 21, we repeat the analysis in Table 4, but for all our investor groups. We omit the first stage regression results here, as it would be the same for each group (see Section 4.1 for the first stage estimates). Broadly, our takeaway from Table 21 is that the results from the OLS regressions in the main body of the paper are mostly qualitatively unchanged in the IV setting. Firms are still the most responsive to Index Fund demand, as they have the most negative IV estimate of any group. Active Funds, Insurance, and Pensions still have positive coefficients, i.e., trade in the same direction as Index Fund demand.

Two notable differences with the IV results from the OLS results are Short Sellers and Other. In Table 21, the coefficient on Short Sellers is positive and insignificant, while in the baseline OLS specification the coefficient is negative. One explanation for this change is that our IV identifies "non-fundamental" demand shocks, and Short Sellers, as smart money, focus on betting against fundamental shocks (Hanson and Sunderam, 2014). An additional change is that the coefficient for Other has become much larger in magnitude, going from -0.25 to -0.85. One possible explanation for this change is that clearing the market for non-fundamental demand shocks relies more heavily on the Other category. However, we must highlight that with the IV, there is no observation-by-observation enforcement of market clearing, as the instrumented Index Fund demand is not used to compute the Other category. Therefore, residuals in the first stage may be correlated with our Other category – explaining the larger (in magnitude) coefficient in the IV setting.

C.2 IV with only past returns

As mentioned in the main body of the paper, one may be concerned about our use of both lagged ($t-1$) and contemporaneous (t) returns to predict Index Fund demand in quarter t. One possible problem is that the "exogenous" (i.e., instrumented) Index Fund demand causes high returns in the focal stock i at time t, which leads to flows into the index funds $k \in K$ which hold stock i. Then, it is possible that these flows (caused by the flow-based price pressure on the focal stock) put price pressure on the unrelated co-holdings and lead to even more flows into index funds $k \in K$. In this scenario, the instrument may be partly picking up reverse causality, violating the exclusion restriction in our IV setup.

To construct a version of the IV insulated from this reverse causality problem, we replicate the results in Table 4, but modify the first stage regression to only use "leave-out" co-holdings returns at $t-1$. Even if these lagged returns lead to price pressure on the focal stock i in quarter t, which

Table 21: Instrumental Variables Specification – All Investor Groups

	Act. Fnds. (1)	Oth. Fnds. (2)	Pens. (3)	Ins. (4)	Fin Inst. (5)	Insiders (6)	Others (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.477***	0.0989	0.0479**	0.108**	-0.0627	-0.213***	-0.835***	0.243	-0.864**
	(0.123)	(0.113)	(0.023)	(0.045)	(0.412)	(0.055)	(0.311)	(0.205)	(0.389)
$SUE_{i,t}$	0.0130***	0.00142**	0.000805*	0.00571***	0.0240***	-0.00354**	-0.0550***	0.003	0.0105**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.006)	(0.001)	(0.014)	(0.006)	(0.005)
$SUE_{i,t-1}$	0.00700**	0.00179***	0.000	0.000	0.002	-0.00356***	-0.019	-0.003	0.0145**
	(0.003)	(0.001)	(0.000)	(0.000)	(0.006)	(0.001)	(0.011)	(0.002)	(0.006)
Observations	130,794	130,794	130,794	130,794	130,794	130,794	130,794	130,794	130,794
R-squared	-0.017	0	-0.004	0.004	0.001	-0.012	-0.014	-0.042	0.026
Fixed Effects	FF 10 by YQ								

Notes. The table provides estimates from the second stage of our IV regression:

$$q_{i,j,t} = \beta \cdot \bar{q}_{i,IDX,t} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + \varepsilon_{i,j,t},$$

where $\hat{q}_{i,IDX,t}$ is the instrumented Index Fund demand based on weighted average leave-out co-holdings returns in quarters $t-1$ and t. $SUE_{i,t}$ is the standardized unexpected earnings (SUE) of stock i in quarter t. FE are a set of Fama-French 10 industry-by-year-quarter fixed effects. Standard errors are double-clustered at the stock and time (year-quarter) level.

in turn feeds back into the unrelated co-holdings' returns in t, the IV will not use this variation to predict Index Fund demand in stock i in quarter t. We still control for SUE at t because it is not clear how flows would have a causal effect on contemporaneous SUE (i.e., how the reverse causality would be relevant for the focal firm's *fundamentals*). Before discussing the results, we want to highlight that this is a much higher bar than our original IV design. As we show in Appendix C.3, the flow-performance relationship is significant for both current and past returns. Omitting contemporaneous returns, therefore, introduces noise, weakening the instrument.

With that said, we report the results of this alternative IV design in Table 22. For ease of comparison, the left panel replicates the results in Table 4. The right panel contains the results when omitting the contemporaneous leave-out co-holdings returns. By omitting the contemporaneous co-holdings returns, the first stage becomes weaker, with the F-statistic dropping from 23.3 to 11.7. However, it remains above the standard threshold of 10 for weak instruments. The estimated IV coefficient becomes larger in magnitude but less statistically significant. The increase in the magnitude of the IV coefficient is likely due to the instrument becoming weaker (i.e., because the denominator in $X'Y/X'Z$ is closer to zero). However, the IV estimate remains marginally significant. Finally, the reduced form still retains marginal significance and predicts Firm demand with the expected sign. In all, Table 22 shows our IV results are robust to this higher bar of using only lagged leave-out co-holdings returns to predict Index Fund demand.

Table 22: Instrumental Variables Specification: Robustness to Using Only Past Returns

	Baseline IV specification			IV using only coholdings returns at $t-1$		
	First Stage	IV	RF	First Stage	IV	RF
$\overline{r}_{i,t-1}^{coholdings}$	1.045***		-1.433*	1.034***		-1.427*
	(0.253)		(0.842)	(0.303)		(0.854)
$\overline{r}_{i,t}^{coholdings}$	1.567***		-1.004			
	(0.330)		(0.758)			
$SUE_{i,t}$	0.00463***	0.0105**	0.006	0.00477***	0.0129**	0.006
	(0.001)	(0.005)	(0.005)	(0.001)	(0.005)	(0.005)
$SUE_{i,t-1}$	0.00373***	0.0145**	0.0112**	0.00388***	0.0164**	0.0111**
	(0.001)	(0.006)	(0.005)	(0.001)	(0.007)	(0.005)
$q_{i,IDX,t}$		-0.864**			-1.379*	
		(0.389)			(0.782)	
Observations	130,794	130,794	130,794	130,794	130,794	130,794
R-squared	0.1	0.026	0.033	0.096	-0.013	0.033
F-statistic	23.26			11.66		
Fixed Effects	FF 10 by YQ			FF 10 by YQ		

Notes. The table provides our baseline IV estimates, as well as estimates from the first and second stages of our IV regression using only past returns, along with the associated reduced form regressions:

$$q_{i,IDX,t} = \gamma_{t-1} \cdot \overline{r}_{i,t-1}^{coholdings} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + e_{i,t},$$

$$q_{i,Firm,t} = \beta \cdot \hat{q}_{i,IDX,t} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + \varepsilon_{i,Firm,t},$$

where $\overline{r}_{i,t-1}^{coholdings}$ is the weighted average leave-out co-holdings returns across all index funds $k \in K$ that held stock i at the end of quarter t. $SUE_{i,t}$ is the standardized unexpected earnings (SUE) of stock i in quarter t. FE are a set of Fama-French 10 industry-by-year-quarter fixed effects. Standard errors are double-clustered at the stock and time (year-quarter) level. In each panel, the first column reports the first stage regression, and the last row reports the associated F-statistic. The second column reports the IV specification, while the third column reports the reduced form regression. The left panel replicates our baseline IV results, while the right panel uses only past leave-out co-holdings returns.

C.3 Flow-Performance Relationship

As highlighted in Section 4.1, our baseline IV essentially takes the flow performance relationship as given. In this subsection, we aim to refine that result by explicitly estimating the flow performance relationship for each fund. To this end, we run the following regression separately for each fund k:

$$flow_{k,t} = \alpha_k + \beta_{1,k} r_{k,t} + \beta_{2,k} r_{k,t-1} + e_{k,t}, \tag{20}$$

where $flow_{k,t}$ is the percentage flow – i.e., flow as a percentage of lagged AUM (Barber et al., 2016) – into fund k between the end of quarter $t-1$ and the end of quarter t. $r_{k,t}$ and $r_{k,t-1}$ are the quarter t and quarter $t-1$ returns for fund k.

Empirically, there is significant variation in $\beta_{1,k}$ and $\beta_{2,k}$ across funds. To visualize this, in Figure 14 we split the sample by "pure" (or broad-based) and "systematic" (or style) funds, and then further split each sample into 20 groups based on the average number of holdings in each fund. The data points on the left represent funds with a small number of holdings, while the data points on the right represent funds with a large number of holdings. Pure or broad-based index funds are defined as the broad capitalization-based funds for the S&P 500, 400, 600, the Russell 1000, 2000, and the CRSP-Capitalization-Based indices used by Vanguard. Systematic or style funds, include, e.g., sector and factor ETFs.

Three important patterns emerge in Figure 14. First, the flow performance relationship is stronger in funds with fewer holdings. Second, for pure capitalization-based funds, the flow performance relationship is non-existent or even negative. This latter fact may at first seem bizarre, but, as a reminder, these are *slopes*. The growth of, e.g., VTI may come through regular employee 401K contributions which are unrelated to VTI's performance, and therefore may show up in the α_{VTI} of Equation 20. Finally, $\beta_{1,k}$ and $\beta_{2,k}$ are of similar magnitudes, suggesting that both last quarters' and this quarters' performance are relevant for predicting flows.

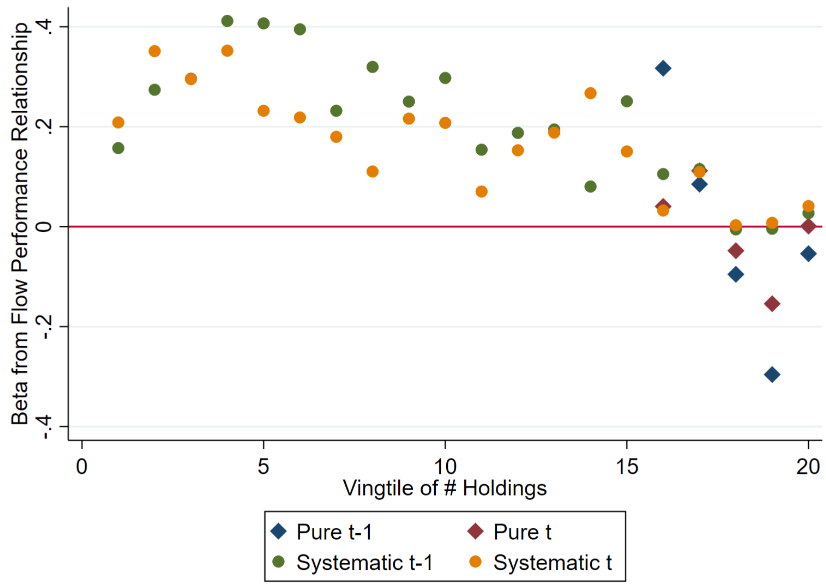
We then use $\beta_{1,k}$ and $\beta_{2,k}$, along with the leave-out co-holdings returns, to predict the part of flows coming from the performance of stock i's unrelated co-holdings. Specifically, for stock i in quarter t for fund k, the predicted flow is

$$\widehat{flow}_{i,k,(t-1,t)} = \beta_{1,k} \cdot r^{coholdings}_{i,k,t} + \beta_{2,k} \cdot r^{coholdings}_{i,k,t-1}.$$

Note, that even though each fund only has one estimated flow performance relationship ($\beta_{1,k}$ and $\beta_{2,k}$), predicted flows $\hat{flow}_{i,k,(t-1,t)}$ for each focal stock i and quarter t will be different because it will be estimated with different leave-out co-holdings returns (which depend on a stock and its characteristics and industry).

We then use these estimated flows to predict trading by each fund – which, given that value-weighted index funds scale up and down positions in proportion to flows, should be $\widehat{flow}_{k,(t-1,t)} \cdot$

Figure 14: Flow Performance Relationship by Vigintile of Holdings



Notes. The figure shows the estimated flow performance relationship ($\beta_{1,k}$ and $\beta_{2,k}$) by vigintile of fund holdings. Vigintile 1 represents funds with fewer holdings, while the vigintile 20 represents funds with the largest number of holdings.

Shares Held$_{i,k,t-1}$. Finally, we aggregate across all index funds $k \in K$ that held stock i at the end of quarter t, and normalize by lagged shares outstanding to make the units consistent with $q_{i,IDX,t}$:

$$\tilde{q}_{i,t} = \sum_{k \in K} \widehat{flow}_{i,k,(t-1,t)} \cdot \text{Shares Held}_{i,k,t-1} / \text{Shares Out.}_{i,t-1} \tag{21}$$

To reduce the effect of outliers, we Winsorize $\tilde{q}_{i,t}$ at the 0.5% and 99.5% level. As an additional robustness check – to avoid the possible reverse causality issue discussed in Section C.2 – we also construct a version of predicted flows in Equation 20 using only past leave-out co-holdings returns.

Ultimately, we want to run a regression of Firm demand on our predicted measure of Index Fund demand, or

$$q_{i,Firm,t} = \beta \cdot \tilde{q}_{i,IDX,t} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + \varepsilon_{i,Firm,t}. \tag{22}$$

We report the results in Table 23. The left panel uses both co-holdings returns at $t-1$ and t in the flow performance relationship. The first column reports the first stage, showing that our measure of predicted flow-based trading is strongly correlated with actual Index Fund demand. The coefficient of 0.857 implies that for every 1 percentage point of market capitalization we expect to be demanded by Index Funds, they actually demand 86 basis points. Also note that the F-statistic is larger than in Table 4 – suggesting that leveraging the observed flow performance relationship allows us to more accurately predict Index Fund demand.

Table 23: Predicting Index Fund Flows Using Fund-Level Flow Performance Relationship

	t and $t-1$ Returns		$t-1$ Returns	
	First Stage	"IV"	First Stage	"IV"
$\tilde{q}_{i,IDX,t}$	0.857***	-0.883***	0.875***	-0.852**
	(0.123)	(0.247)	(0.265)	(0.357)
$SUE_{i,t}$	0.00449***	0.00669	0.00447***	0.0067
	(0.001)	(0.005)	(0.001)	(0.005)
$SUE_{i,t-1}$	0.00382***	0.0112**	0.00386***	0.0111**
	(0.001)	(0.005)	(0.001)	(0.005)
Observations	130,794	130,794	130,794	130,794
R-squared	0.099	0.033	0.096	0.033
F-statistic	48.26		10.88	
Fixed Effects	FF 10 by YQ		FF 10 by YQ	

Notes. The table provides estimates from the first stage and reduced form regressions using predicted passive flows based on fund-level flow performance relationships:

$$q_{i,Firm,t} = \beta \cdot \tilde{q}_{i,IDX,t} + \psi_1 \cdot SUE_{i,t} + \psi_2 \cdot SUE_{i,t-1} + \text{FE} + \varepsilon_{i,Firm,t},$$

where $\tilde{q}_{i,IDX,t}$ is the predicted Index Fund demand based on the estimated flow performance relationships and leave-out co-holdings returns. $SUE_{i,t}$ is the standardized unexpected earnings (SUE) of stock i in quarter t. FE are a set of Fama-French 10 industry-by-year-quarter fixed effects. Standard errors are double-clustered at the stock and time (year-quarter) level. The left panel uses both contemporaneous and lagged co-holdings returns to predict flows, while the right panel uses only lagged co-holdings returns to predict flows.

In this setting, we do not use a traditional two-stage least-squares estimate, as our measure of expected index fund demand is already a prediction using our co-holdings returns as a type of instrument, and is in the same units as $q_{i,IDX,t}$. In this sense, Equation 22 is our "second-stage IV" estimate but looks like a reduced form regression – in that we are directly regress Firm demand on our measure of predicted Index Fund demand – which is why we label these columns RF. These results are in the second column. We find a coefficient of -0.88, which is very similar in magnitude to our OLS regression. This confirms the results in 4, and further allays concerns of the IV estimate being distorted by the difference in units between returns and Index Fund demand.

Finally, in the right panel, we repeat this exercise but only estimate the flow performance relationship using each fund's $t-1$ returns, and then predict flows given leave-out co-holdings returns at $t-1$. Unsurprisingly, we find a weaker first stage, but again, this "alternative" IV-style regression is quantitatively unchanged. This further suggests that reverse causality in quarter t is not driving the strength of our IV results.

C.4 Mechanical Relationship between Shorting and Passive Ownership

As shown in the main body of the paper – increases in passive ownership seem to be accommodated by short selling, i.e., some part of the shares demanded by passive investors are created through increased short interest. One concern with these results is that there is a mechanical relationship between increases in passive ownership and short selling. Specifically, as previously documented (see, e.g., Palia and Sokolinski (2021), von Beschwitz et al. (2022)) passive funds are able to lend out a fraction of the shares they hold to generate additional income and this may lead to higher short interest in high passive ownership stocks.[33]

To test this, we leverage data from Markit (also used in, e.g., Muravyev et al. (2022)) on short interest, estimated quantities of shares available for lending, utilization rates and expected borrowing costs. We start with a straightforward cross-sectional regression of these quantities on passive ownership, non-passive institutional ownership, firm size, percentage growth in firm market capitalization over the past 12 months, firm fixed effects and time fixed effects.

The results are in Table 24. The first column includes the results for the short interest ratio (SIR), defined as the ratio of the number of shares shorted to the number of shares outstanding (Hanson and Sunderam, 2014). The point estimate is positive and significant, suggesting that a 1% increase in passive ownership is correlated with a 9 basis point increase in SIR. Overall non-passive institutional ownership is also correlated with higher levels of short interest, consistent with evidence in Daniel et al. (2021).

Column 2 shows the results for the estimated supply of lendable shares, defined as Markit's estimate of shares available for lending divided by shares outstanding. Again, the point estimate is positive and significant, suggesting that a 1% increase in passive ownership is correlated with a 77 basis point increase in the amount of lendable shares. The results in columns 1 and 2 are already evidence against a purely mechanical effect of passive ownership on short interest. For example, if passive funds lent out exactly 30% of the shares they owned, we would expect a point estimate of around 30. Of course, passive funds can lend out 30% of the value of their portfolio. And, it may be that this is not distributed equally among all their holdings.

Column 3 shows the results for the utilization rate, defined as the quantity shorted divided by Markit's estimate of the number of lendable shares. The point estimate is negative and significant, suggesting that a 1% increase in passive ownership is correlated with an 18 basis point decrease in utilization. While this initially seems counter intuitive, it makes sense given the results in columns 1 and 2: short interest increases, but the amount of lendable shares increases more, so utilization goes down. Finally, column 4 shows that higher levels of SIR are correlated with higher shorting

[33] As discussed in Appendix B of Blocher and Whaley (2015), Sec 18 of the 1940 Act would allow passive funds to lend out up to 30% of the value of their portfolio. Later interpretations of this rule suggest it would be possible to lend out up to 50% of the portfolio value, due to the fact that the collateral received against the securities lent effectively increase the assets of the portfolio, and therefore increase the amount of lending that could be done.

Table 24: Shorting and Passive Ownership in the Cross-Section

	%Shrout		%Lendable	
	SIR	Lendable	Util.	Cost
	(1)	(2)	(3)	(4)
SIR				0.41***
				(0.03)
Pass	0.09***	0.77***	-0.18***	-0.22***
	(0.01)	(0.03)	(0.04)	(0.02)
Othr. Inst.	0.06***	0.06***	0.06***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
ln(1+Mkt. Cap.)	-0.00***	0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
% Ch. Mkt. Cap.	-0.01***	-0.02***	0	0.03***
	(0.00)	(0.00)	(0.01)	(0.01)
Observations	220,562	220,562	220,562	220,562
R-squared	0.584	0.889	0.529	0.51
Permno FE	YES	YES	YES	YES
YQ FE	YES	YES	YES	YES

Notes. Cross sectional regression of the short interest ratio (SIR), the supply of lendable shares (Lendable), the utilization rate (Util) and shorting cost (Cost) on passive ownership and control variables. The short interest ratio is defined as the ratio of the number of shares shorted to the number of shares outstanding (Hanson and Sunderam, 2014). The supply of lendable shares is defined as Markit's estimate of shares available for lending divided by shares outstanding. The utilization rate is defined as the quantity shorted divided by Markit's estimate of the number of lendable shares. Expected shorting costs are defined as the Indicative Fee variable provided by Markit. The unit of observation is stock-quarter.

costs, and generally, stocks with more passive ownership have lower shorting costs.

Collectively, the results in Table 24 suggest that our results on short interest increasing to accommodate passive ownership are not a mechanical function of passive funds themselves lending out their shares. First, the magnitudes in column 1 are not large enough to explain our findings. Second, the negative relationship with utilisation in column 3 suggests that even if the lendable quantity of shares increases in high passive stocks, this is likely not a binding constraint for investors who would like to short.

C.5 Responsiveness to Prices by Net Index Fund Buying and Selling

In this subsection, we replicate the results in Section 5.1, restricting to firm-quarter observations where Index Funds are either net buyers or net sellers. In Table 25, we show that the effect of excess earnings yield on Firms' responsiveness is entirely driven by the subsample with net Index Fund buying. Specifically, we see the interaction term for Index Fund demand and earnings yield is large, negative and significant in Panel A (the net passive buying subsample), while it is small and insignificant in Panel B (the net passive selling subsample.

Table 25: Earnings Yield and Market Clearing, split by Net Index Fund Buying and Selling

Panel A: Index Funds Net Buyers

	Act. Fnds. (1)	Oth. Fnds. (2)	Pens. (3)	Ins. (4)	Fin Inst. (5)	Insiders (6)	Others (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.255***	0.114***	0.0244***	0.0695***	0.198**	-0.0859***	0.117*	-0.348***	-1.345***
	(0.039)	(0.022)	(0.005)	(0.009)	(0.081)	(0.013)	(0.070)	(0.047)	(0.081)
$1_{EXEY_{i,t}>0}$	-0.101***	-0.0241	-0.0280***	-0.0252**	-0.117	0.0022	-0.407***	0.000796	0.699***
	(0.033)	(0.018)	(0.007)	(0.011)	(0.076)	(0.012)	(0.082)	(0.041)	(0.074)
$q_{i,IDX,t} \times 1_{EXEY_{i,t}>0}$	-0.125**	0.00168	0.000607	0.00749	-0.648***	0.0077	-0.196**	0.145***	0.806***
	(0.053)	(0.050)	(0.005)	(0.016)	(0.079)	(0.015)	(0.078)	(0.038)	(0.075)
Observations	107,053	107,053	107,053	107,053	107,053	107,053	107,053	107,053	107,053
R-squared	0.007	0.014	0.006	0.007	0.009	0.003	0.005	0.014	0.088
Fixed-Effects					YQ				

Panel B: Index Funds Net Sellers

	Act. Fnds. (1)	Oth. Fnds. (2)	Pens. (3)	Ins. (4)	Fin Inst. (5)	Insiders (6)	Others (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.196***	0.0333***	0.0201***	0.0507***	-0.0892	-0.0207	-1.133***	-0.190***	0.133**
	(0.034)	(0.012)	(0.007)	(0.013)	(0.093)	(0.016)	(0.141)	(0.063)	(0.051)
$1_{EXEY_{i,t}>0}$	-0.0673**	0.0053	-0.0316***	-0.0366***	-0.471***	-0.0374**	-0.432***	0.0338	1.036***
	(0.032)	(0.012)	(0.007)	(0.012)	(0.086)	(0.014)	(0.107)	(0.043)	(0.091)
$q_{i,IDX,t} \times 1_{EXEY_{i,t}>0}$	-0.0252	-0.00575	-0.0333***	-0.0207	-0.507***	-0.00349	0.592***	0.0639	-0.0611
	(0.050)	(0.016)	(0.005)	(0.014)	(0.093)	(0.016)	(0.115)	(0.048)	(0.061)
Observations	39,821	39,821	39,821	39,821	39,821	39,821	39,821	39,821	39,821
R-squared	0.003	0.001	0.002	0.002	0.007	0.001	0.032	0.003	0.043
Fixed-Effects					YQ				

Notes. The table provides estimates from our baseline OLS regression augmented to account for the effect of relative valuation on each groups' response to Index Fund demand. We estimate

$$q_{i,j,t} = \beta_j q_{i,IDX,t} + \gamma_j 1_{EXEY_{i,t}>0} + \psi_j q_{i,IDX,t} \times 1_{EXEY_{i,t}>0} + \rho_t + e_{i,j,t},$$

where $EXEY_{i,t}$ is firm i's excess earnings yield in year-quarter t, defined as the difference between the firm's trailing 12-month earnings yield and the risk-free rate, as measured by the yield on 10-year Treasuries. ρ_t are a set of year-quarter fixed effects. Panel A restricts to stock-quarters with net Index Fund buying, while Panel B restricts to stock-quarters with net Index Fund selling. Standard errors are double clustered at the stock and year-quarter level. See Section 5.1 for more details on the table.

Table 26 shows an even more striking difference for the effects of Tobin's Q depending on whether Index Funds are net buyers or sellers. In Panel A, the sample with net Index Fund buying, the coefficient on the interaction term between Index Fund demand and the top Tobin's Q quintile is large, negative and statistically significant. On the other hand, in Panel B, the sample with net Index Fund selling, the coefficient flips sign, becoming positive and significant. Collectively, the evidence in Table 25 and Table 26 suggests that the results in Section 5.1 are driven by Firms being more willing to accommodate Index Fund buying when valuations are relatively high.

Table 26: Tobin's Q and Market Clearing, split by Net Index Fund Buying and Selling

	Panel A: Index Funds Net Buyers								
	Act. Fnds. (1)	Oth. Fnds. (2)	Pens. (3)	Ins. (4)	Fin Inst. (5)	Insiders (6)	Others (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.128***	0.0649***	0.0256***	0.0644***	-0.00716	-0.0879***	-0.0759	-0.313***	-0.799***
	(0.029)	(0.014)	(0.004)	(0.007)	(0.088)	(0.016)	(0.058)	(0.034)	(0.075)
$q_{i,IDX,t} \times 1_{QQ=1,i,t-1}$	-0.0603*	-0.0393***	-0.00305	-0.0150*	-0.161**	0.0407*	-0.0391	0.00948	0.267***
	(0.030)	(0.011)	(0.004)	(0.008)	(0.076)	(0.022)	(0.084)	(0.033)	(0.100)
$q_{i,IDX,t} \times 1_{QQ=2,i,t-1}$	-0.00539	-0.01	0.00147	-0.00954	-0.0771	0.0346*	-0.0822	0.0149	0.133**
	(0.023)	(0.009)	(0.004)	(0.010)	(0.065)	(0.018)	(0.052)	(0.025)	(0.066)
$q_{i,IDX,t} \times 1_{QQ=4,i,t-1}$	0.122***	0.0377***	0.0171***	0.0127	0.214***	-0.0657***	0.103	-0.128***	-0.313***
	(0.028)	(0.011)	(0.005)	(0.009)	(0.072)	(0.022)	(0.072)	(0.028)	(0.084)
$q_{i,IDX,t} \times 1_{QQ=5,i,t-1}$	0.238***	0.0506***	0.0194***	0.0280***	0.345***	-0.0980***	0.0225	-0.130***	-0.475***
	(0.034)	(0.014)	(0.004)	(0.009)	(0.079)	(0.026)	(0.072)	(0.032)	(0.092)
Observations	121,819	121,819	121,819	121,819	121,819	121,819	121,819	121,819	121,819
Constant	0.027	0.128	0.046	0.038	0.057	0.015	0.04	0.093	0.065
Fixed-Effects	YQ + Tobin's Q Quintile								

	Panel B: Index Funds Net Sellers								
	Act. Fnds. (1)	Oth. Fnds. (2)	Pens. (3)	Ins. (4)	Fin Inst. (5)	Insiders (6)	Others (7)	Shorts (8)	Firms (9)
$q_{i,IDX,t}$	0.171***	0.0340**	0.00258	0.0530***	-0.541***	-0.00654	-0.751***	-0.0481	0.0857**
	(0.049)	(0.015)	(0.008)	(0.015)	(0.121)	(0.015)	(0.135)	(0.053)	(0.043)
$q_{i,IDX,t} \times 1_{QQ=1,i,t-1}$	0.0684	0.00505	0.0235**	0.00825	0.360***	-0.029	-0.433***	-0.00902	0.00587
	(0.058)	(0.019)	(0.009)	(0.015)	(0.115)	(0.022)	(0.154)	(0.060)	(0.048)
$q_{i,IDX,t} \times 1_{QQ=2,i,t-1}$	0.0325	0.0152	0.00815	0.00352	0.0322	-0.0271	0.0241	-0.0860**	-0.00256
	(0.053)	(0.018)	(0.007)	(0.017)	(0.121)	(0.021)	(0.134)	(0.043)	(0.052)
$q_{i,IDX,t} \times 1_{QQ=4,i,t-1}$	0.0308	-0.0293*	-0.00669	-0.0181	0.0737	0.0112	-0.0215	-0.172***	0.132*
	(0.055)	(0.017)	(0.009)	(0.019)	(0.118)	(0.025)	(0.121)	(0.048)	(0.069)
$q_{i,IDX,t} \times 1_{QQ=5,i,t-1}$	-0.110**	-0.0592***	-0.0146	-0.0135	0.116	0.00919	-0.103	-0.0768	0.252***
	(0.047)	(0.022)	(0.009)	(0.018)	(0.102)	(0.026)	(0.139)	(0.059)	(0.091)
Observations	44,966	44,966	44,966	44,966	44,966	44,966	44,966	44,966	44,966
Constant	0.019	0.038	0.05	0.029	0.054	0.01	0.06	0.065	0.019
Fixed-Effects	YQ + Tobin's Q Quintile								

Notes. The table provides estimates from our baseline OLS regression augmented to account for the effect of Tobin's Q on each groups' response to Index Fund demand:

$$q_{i,j,t} = \beta_j \cdot q_{i,IDX,t} + \sum_g \gamma_{j,g} \cdot \mathbb{1}_{QQ=g,i,t-1} + \sum_g \psi_{j,g} \cdot \mathbb{1}_{QQ=g,i,t-1} \cdot q_{i,IDX,t} + \rho_t + e_{i,j,t},$$

where $\mathbb{1}_{QQ=g,i,t-1}$ is an indicator variable that equals 1 if stock i is in Tobin's Q quintile g at the end of quarter $t-1$. The middle group, i.e., $QQ = 3$ is the omitted category. ρ_t are a set of year-quarter fixed effects. Panel A restricts to stock-quarters with net Index Fund buying, while Panel B restricts to stock-quarters with net Index Fund selling. Standard errors are double clustered at the stock and time (year-quarter) level.

D Buybacks vs. Issuance

D.1 Stylized Facts on Buybacks vs. Issuance

As we show in Sections 3.1 and in Appendix B.3, Firms' responsiveness to Index Fund demand is similar on both an equal-weighted and value-weighted basis. At first glance, this seems hard to square with two well-known trends. The first is the rise of passive ownership, which went from nearly nothing in the early 1990s to owning nearly 17% of the US stock market in 2021 (Investment Company Institute, 2023). The second trend is the substantial increase in the dollar value of buybacks over the past 20 years (see, e.g., see the Financial Times, Guru Focus, and New York Life). The apparent conflict is that if, on a value-weighted average basis, Firms have been buying back shares *and* Index Funds have been buying shares, how can Firms' demand be the most responsive to Index Funds on average? Further, it seems difficult to reconcile these trends with our main results that – on an equal-weighted basis – Firms have been the largest overall supplier of shares to Index Funds.

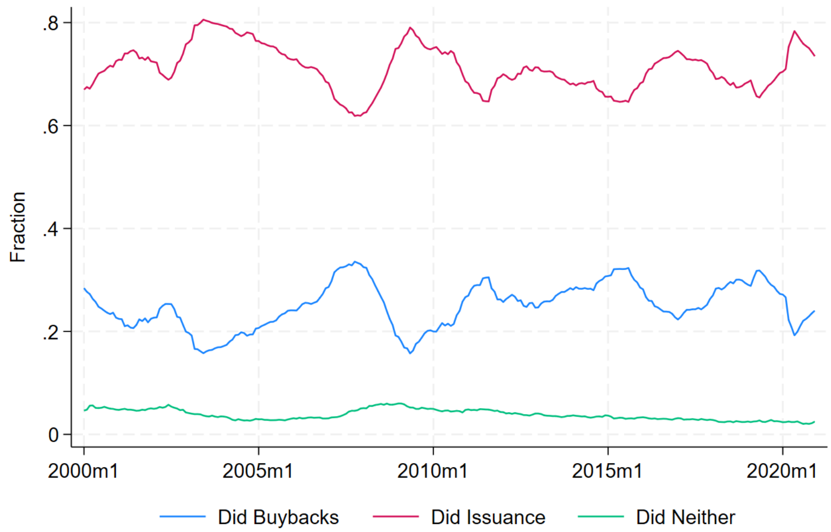
In this appendix, we resolve this conflict by highlighting two important stylized facts. First, in every year in our sample, a significantly larger *number* of firms issue shares than buy back shares. Second, the average size of issuance is larger than the average size of buybacks. Together, these facts imply that the equal-weighted average firm in our sample has actually issued shares, and thus could have been the largest provider of shares to Index Funds who demanded shares on average.

The first natural question we answer is which *fraction* of firms conducts buybacks or issuance each year. In a given month, we classify a firm as doing buybacks over the next year if its split-adjusted shares outstanding has declined 12 months in the future. Similarly, we classify a firm as doing issuance over the next year if its split-adjusted shares outstanding are higher 12 months in the future. Finally, we say that a firm has done neither if split adjusted shares outstanding are constant 12 months in the future. We use a 12-month horizon – instead of, say, a quarterly horizon – to reduce the noise inherent in using possibly stale split-adjusted shares outstanding data in CRSP and to account for seasonalities.

Figure 15 plots the fraction of firms in each of these three categories since 2000. The first salient feature of this figure is that the fraction of firms doing neither buybacks nor issuance has been steadily declining. At the same time, there has been a slight upward trend in the fraction of firms doing buybacks or issuance. Another striking takeaway from this figure is that the fraction of firms doing buybacks is relatively small, hovering between 20 and 30 percent over the last few years. So, while the firms doing buybacks may have been doing more and more in dollar terms, they are still a relatively small fraction of the universe of firms we consider in this paper.

Figure 15 says nothing about the relative magnitudes of these phenomena. Specifically, it could be that each year, many firms are issuing relatively small amounts of equity, while a few firms are

Figure 15: Fraction of Firms Doing Buybacks and Issuance



Notes. Fraction of firms which, over the next year, will do net buybacks, net issuance, or neither. A firm is classified as having net issued equity if it has a year-over-year increase in split-adjusted shares. A firm is classified as having done a net buyback if it has a year-over-year decrease in split-adjusted shares. A firm is classified as having done neither if there has been no change in split-adjusted shares.

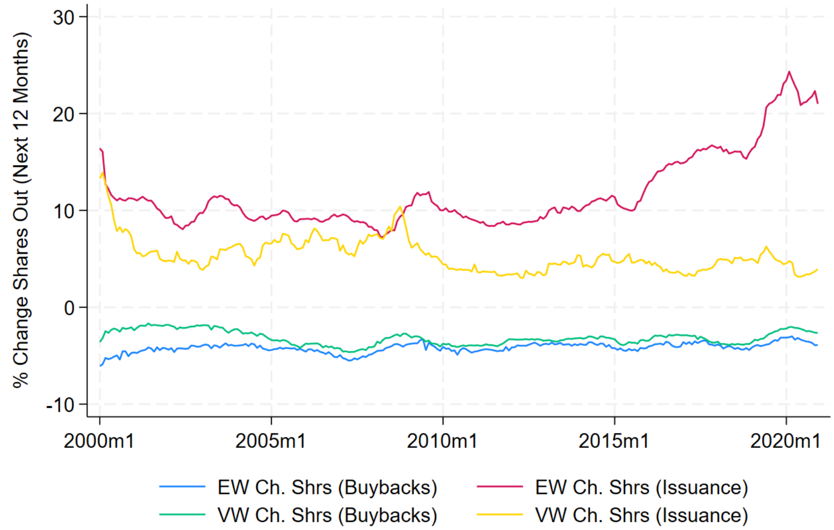
buying back a significant amount of equity, so the overall net effect (on a value-weighted basis) is towards fewer shares outstanding. To examine this, we plot the equal-weighted and value-weighted percentage change in shares outstanding for firms that issue or buyback in Figure 16. Perhaps surprisingly, not only is the fraction of firms doing issuance larger than the fraction of firms doing buybacks, the average magnitude of issuance is larger than the average magnitude of buybacks – especially on an equal-weighted average basis.

Putting together the results in Figures 15 and 16, the final natural question we study is whether there is issuance or buybacks *in aggregate*. To make buybacks and issuance comparable across firms, we first redefine these quantities to be in dollar terms. To do this, we need an assumption about the price firms paid for buybacks/received for issuance, so we assume that firms transact at the dollar volume weighted average split-adjusted price over the next 12 months. We then multiply the change in split-adjusted shares outstanding over the next 12 months by this average price to get an estimate of buybacks/issuance in dollars. Finally, we add this up across firms for each month to get a measure of net dollar issuance or buybacks.[34]

Figure 17 plots the total dollar amount for all firms that issued shares, bought back shares, and a signed net (aggregate buybacks minus aggregate issuance). Leading into the Global Financial Crisis,

[34] One might be concerned that there is some bias in using the average price over the next 12 months to estimate dollar buybacks/issuance. Specifically, one might think that we are overstating net buybacks if firms that do buybacks have stock price increases, and firms that do issuance have stock price decreases. Our methodology, however, yields almost identical estimates for the amount of buybacks by S&P 500 firms in this chart, which is based on data directly from S&P Dow Jones.

Figure 16: Magnitudes of Buybacks and Issuance (Relative to Shares Outstanding)



Notes. Firms are split into groups based on whether they net issued shares (i.e., had an increase in split-adjusted shares outstanding) or net bought back shares (i.e., had a decrease in split-adjusted shares outstanding) over the next year. For each group, we plot the equal-weighted and value-weighted average percentage change in shares outstanding over the next 12 months. For the value-weighted averages, each firm's weight is proportional to that firms' share of total market capitalization *in the buyback or issuance group* in quarter $t-1$.

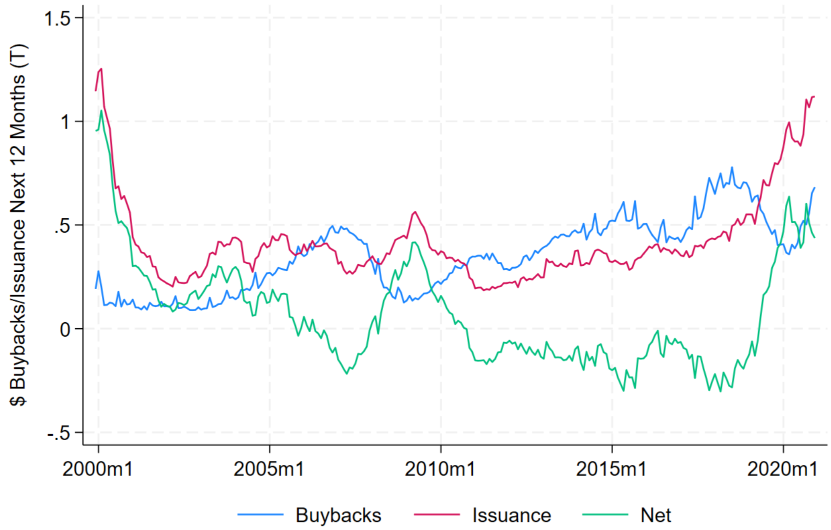
buybacks grew significantly, becoming larger than issuance. This temporarily reversed during and after the Global Financial Crisis, and then switched back to a buyback-heavy regime from around 2011 to 2019. Finally, many firms issued equity during the COVID-19 crisis.

At first glance, Figure 17 might deepen the puzzle outlined at the beginning of this section. Passive ownership grew significantly, i.e., passive funds had to buy a significant fraction of each firm's shares outstanding, and at the same time, there were net aggregate dollar buybacks by firms. These trends still seem hard to reconcile with our main results, which show that firms have provided liquidity to passive ownership. Recall, however, that the bulk of our analysis is effectively equal-weighted. This is one explanation for how, in dollar terms, buybacks may have dominated issuance, but for the (equal-weighted) average firm, issuance has been more prevalent than buybacks. This is supported by Figure 15, which shows that more firms issue than buy back shares, and Figure 16, which shows that the average size of issuance is larger than buybacks.

D.2 Firms with Buyback Programs

In this subsection, we provide additional results on the decomposition in Section 5. As shown in Figure 15, a relatively small fraction of firms do buybacks each quarter. Therefore, one might be concerned that the small coefficient in Table 7 for buybacks is the result of buybacks themselves being relatively less common – at least on an equal-weighted average basis.

Figure 17: Total Dollar Value of Buybacks and Issuance



Notes. Firms are split into groups based on whether they net issued shares (i.e., had an increase in split-adjusted shares outstanding) or net bought back shares (i.e., had a decrease in split-adjusted shares outstanding) over the next year. We assume that firms do buybacks and issuance at the volume-weighted average split-adjusted price over the next year. The lines represent the estimated total dollar value of buybacks and issuance over the next 12 months for each group.

To test this, we identify a subsample of firm-quarters where there appears to be a buyback program in place – defined as firm-quarter observations with positive values of PRSTKCY over each of the previous 4 quarters. We then re-run our baseline decomposition on this subsample, further restricting to the 2010-2021 period, as this is when we have data from Bloomberg on SEOs. The results are in Panel A of Table 27. Perhaps unsurprisingly, the importance of buybacks is doubled in the subsample of firms with buyback activity – with the coefficient jumping from -0.18 to -0.36. And, when considering that these these firms are unconditionally less responsive to passive demand than the average firm (Column 1 vs. Column 5), the buybacks channel appears even more important among these firms.

As indicated by Figure 17, even though the number of firms which do buybacks is small, large firms must be doing a significant dollar amount of buybacks, as firms in our sample are buying back shares on net in dollar terms. So in Panel B of Table 27, we replicate our decomposition with value weights. Even before restricting to the subsample with a buyback program in place, buybacks become much more important on a value-weighted average basis, with the coefficient nearly tripling in column 10 relative to column 2. Further, in the subsample with a buyback program in place, we see an even larger coefficient for buybacks when using value weights, explaining nearly half of Firms' overall responsiveness.

Collectively, the evidence in Table 27 suggests that for firms with buyback programs in place, and more generally for large firms, the buyback margin is much more important than the (equal-

Table 27: Beta Estimates: Decomposing Firm Changes

Panel A: Equal Weighted (2010-2021)

	All Observations				Buyback Program Subsample			
	Firms (Overall)	Buybacks	SEOs	Comp + Other	Firms (Overall)	Buybacks	SEOs	Comp + Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index Funds	-1.5	-0.181	-0.119	-1.2	-1.096	-0.359	-0.064	-0.674
	(-20.108)	(-13.885)	(-9.801)	(-17.195)	(-15.188)	(-13.232)	(-4.919)	(-10.519)
Constant	-0.66	2.065	-0.078	-2.647	1.961	4.071	-0.021	-2.089
	(-4.671)	-30.755	(-5.396)	(-23.930)	-9.971	-32.56	(-1.435)	(-16.480)
Observations	102,261	102,261	102,261	102,261	32,287	32,287	32,287	32,287
R-squared	0.107	0.017	0.013	0.079	0.109	0.039	0.009	0.054

Panel B: Value Weighted (2010-2021)

	All Observations				Buyback Program Subsample			
	Firms (Overall)	Buybacks	SEOs	Comp + Other	Firms (Overall)	Buybacks	SEOs	Comp + Other
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Index Funds	-1.523	-0.519	-0.101	-0.903	-1.395	-0.781	-0.057	-0.558
	(-9.936)	(-8.014)	(-7.137)	(-7.445)	(-9.906)	(-8.504)	(-3.884)	(-4.405)
Constant	2.041	3.378	0.009	-1.346	3.141	4.519	0.01	-1.388
	-8.816	-21.078	-0.814	(-8.349)	-16.223	-26.942	-1.5	(-9.889)
Observations	102,261	102,261	102,261	102,261	32,287	32,287	32,287	32,287
R-squared	0.153	0.048	0.014	0.068	0.143	0.075	0.008	0.035

Notes. The table provides estimates from our baseline regression specification:

$$q_{i,j,t} = \alpha_j + \beta_j \cdot q_{i,\text{IDX},t} + \varepsilon_{i,j,t}$$

for each investor group j. We decompose our Firms group into three new components: seasoned equity offerings (SEOs), buybacks, and compensation and other issuance activity. We estimate the set of regressions with no fixed effects (left columns) and with Fama-French 10 industry-by-year-quarter fixed effects. The unit of observation is stock-year-quarter, $q_{i,j,t}$ are measured on a year-over-year basis and the data covers the time period 2010 to 2021. T-statistics are computed based on standard errors which are double clustered at the stock and time (year-quarter) level.

weighted) average firm. This is consistent with evidence in Figure 11, where we see that – on a value-weighted basis – Firms reduce buybacks in the face of Index Fund demand.