Ownership, Liquidity, and Volatility: The Role of Active and Passive Institutions

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Abstract

This paper studies how institutional ownership structure affects stock return volatility through its interaction with market liquidity and trading behavior. I show that passive institutional investors amplify volatility in illiquid stocks by executing mechanical trades that are insensitive to market liquidity, while active institutions help stabilize prices. A theoretical model with endogenous informed trading and systematic passive flows explains these patterns. Empirical results using ownership data from 1980–2022 support the model's predictions. The results suggest that volatility arises not from institutional ownership per se, but from the interaction between ownership structure and liquidity.

KEYWORDS: institutional investors, liquidity, volatility, price impact

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1 Introduction

How does the structure of institutional ownership affect stock return volatility? This paper shows that volatility is amplified when large passive institutional investors execute mechanical trades in illiquid markets lacking sufficient informed investors' participation. In contrast, large active institutional ownership is generally neutral or stabilizing for volatility, particularly in more liquid stocks. These dynamics are increasingly relevant given the transformation of institutional investing. In the United States, institutional ownership of common stocks has grown dramatically over the past four decades, with a small number of large mutual fund families—such as BlackRock, Vanguard, and State Street—now managing a substantial share of equity assets. Much of this growth has come through passive investment vehicles, including ETFs and index funds, which must execute trades in proportion to benchmark weights regardless of market liquidity. While such vehicles offer cost efficiency and diversification to investors, they can also transmit flows mechanically into underlying securities without regard to price impact or liquidity constraints.

To formalize this mechanism, I develop a theoretical model in the spirit of Kyle (1985), extended to allow for heterogeneous liquidity, mechanical trading by passive investors, and endogenous information acquisition by active institutions. In the model, passive ownership amplifies volatility through flow-induced price impact, while informed trading by active institutions can stabilize prices—but only when liquidity is sufficient to make information acquisition worthwhile. The model generates four testable predictions: (1) volatility increases with the share of passive ownership and with illiquidity; (2) informed trading becomes less likely as markets become more passive and illiquid; (3) large, sophisticated active investors stabilize prices when they acquire precise information; and

(4) volatility amplification is most severe when passive ownership is high, liquidity is low, and informed participation breaks down.

Empirically, I test these predictions using panel data on institutional ownership and stock returns from 1980 to 2022. I show that volatility effects attributed to institutional ownership are driven primarily by passive vehicles, and that these effects are concentrated in stocks with lower liquidity rather than uniformly across firm size or capitalization segments. When controlling for liquidity characteristics, the positive association between large institutional ownership and volatility remains positive and significant only among illiquid stocks. Specifically, I separate the aggregate portfolio of mutual fund families into actively managed and passive/ETF components, and find that the volatility impact is primarily associated with passive holdings. In contrast, ownership by active funds and other institution types such as banks or investment companies is not significantly associated with increased volatility and may even have stabilizing effects in liquid markets. These findings provide a more nuanced view of institutional impact, highlighting the importance of ownership structure, investment strategy, and liquidity in explaining volatility amplification—dimensions overlooked in prior literature.

From a policy perspective, the results contribute to a broader understanding of how institutional investment reshapes financial markets. Rather than viewing institutional ownership as uniformly stabilizing or destabilizing, this paper suggests that volatility amplification is not simply a result of institutional ownership per se, but of passive flows interacting with limited liquidity and diminished informed participation. This has implications for how market regulators assess systemic risk, interpret volatility in fragmented markets, and design reporting and stress testing frameworks that account for structural frictions in both trading behavior and market depth.

A potential limitation of the empirical strategy is that the estimated effects may not necessarily capture a causal relationship. The primary specification employed in this paper is a panel predictive regression, which relies on the assumption that the lagged ownership by large institutional investors is weakly exogenous—i.e., the error term is mean independent of past ownership values. However, as noted by Stambaugh (1999) and Hjalmarsson (2010), the presence of fixed effects in such predictive settings introduces a finite-sample bias, potentially distorting inference.

To mitigate this concern, I employ the recursive-demeaning (RD) estimator proposed by Moon and Phillips (2000), which has been shown to reduce bias in panel regressions with persistent regressors. While prior studies have primarily applied the RD estimator in models with one-way fixed effects (e.g., Pástor, Stambaugh, & Taylor, 2015; Zhu, 2018), this paper extends its application to a two-way fixed effects setting to simultaneously account for both stock-specific and time-specific unobserved heterogeneity. Controlling for time-fixed effects is particularly important in the context of return volatility, as common macroeconomic shocks may influence both volatility and institutional ownership, potentially confounding the estimated relationship. Importantly, the main results remain robust and quantitatively similar after applying the RD estimator, suggesting that finite-sample bias is not driving the findings.

Nonetheless, concerns about endogeneity may persist if unobserved factors correlated with both institutional ownership and volatility are omitted from the model. To address this issue, I exploit a quasi-natural experiment based on mergers among financial institutions, which generates plausibly exogenous variation in firms' ownership structures. Specifically, the merger of two managing institutional investors generates a plausibly exogenous increase in ownership by large institutions for stocks that were held by the smaller target institution prior to the merger and held by the larger acquiring institution after the merger. This identification strategy strengthens the case for interpreting the documented associations as reflecting, at least in part, a causal relationship. I find that cap-weighted results is consistent with prior findings, showing that ownership-driven volatility effects are largely confined to less liquid stocks.

The rest of the paper is organized as follows. Section 2 describes data sources and how to construct main variables. Section 3 shows and interprets the results. In Section 4, I discuss the finite-sample bias in the fixed effects model, propose the RD estimator, and further employ the quasi-natural experiment. Section 5 concludes.

2 Theoretical Framework and Hypotheses Development

The interaction between the ownership structure of large institutional investors, mechanical trading pressures, and market liquidity lies at the core of understanding stock return volatility. While large institutions have the potential to stabilize markets by absorbing shocks and engaging in informed trading, the modern dominance of passive vehicles such as ETFs and index mutual funds changes this dynamic fundamentally.

Passive funds must trade mechanically in proportion to index weights in response to investor flows, without discretion to delay, smooth, or selectively execute trades based on market conditions. This flow rigidity distinguishes passive institutions from active managers, who retain the ability to trade strategically based on liquidity availability and arbitrage opportunities. When passive flows meet stocks with limited liquidity—where market depth is thin and price impact is high—the mechanical execution of trades amplifies price volatility.

This volatility amplification mechanism is particularly severe in illiquid stocks. Illiquidity, characterized by a larger price impact of trades, inhibits the absorption of mechanical flows, allowing uninformed trades to move prices more sharply. Prior literature has generally focused on the aggregate size of institutions or the capitalization of stocks, but has not sufficiently emphasized how mechanical passive trading interacts with liquidity constraints to amplify volatility.

I present a stylized model in the spirit of Kyle (1985), extended to incorporate heterogeneous liquidity, mechanical trading by passive institutions, and endogenous information acquisition by active institutional investors. The model captures the interaction between market structure and volatility, and provides conditions under which informed traders choose to participate—or exit—endogenously.

There is a risky asset i with payoff: $v_i \sim \mathcal{N}(0, \sigma^2_{v,i})$. A unit mass of institutional investors participates in trading. A fraction $\theta \in [0, 1]$ of institutions are passive (e.g., ETFs, index funds), while the remaining $1 - \theta$ are active and may acquire private information. Passive investors submit flow-driven orders: $f_i \sim \mathcal{N}(0, \sigma^2_{f,i})$, contributing θf_i to aggregate order flow. Active investors may acquire a private signal: $s_i = v_i + \varepsilon_i, \quad \varepsilon_i \sim \mathcal{N}(0, \sigma^2_{\varepsilon,i})$ at cost $c_i > 0$. The signal precision is:

$$\rho_i = \frac{\sigma^2_{v,i}}{\sigma^2_{v,i} + \sigma^2_{\varepsilon,i}}$$

I assume heterogeneous information capacity among active investors, indexed by a parameter $\phi_i > 0$ that represents their research scale or sophistication. Higher ϕ_i implies lower signal noise:

$$\sigma^2_{\varepsilon,i} = \frac{1}{\phi_i}, \quad \Rightarrow \quad \rho_i = \frac{\sigma^2_{v,i}}{\sigma^2_{v,i} + 1/\phi_i}$$

Thus, larger or more sophisticated active institutions produce more precise signals. An informed active investor, if she chooses to acquire the signal, submits demand: $x_i = \beta_i \rho_i s_i$. Total demand submitted to the market maker is: $q_i = \theta f_i + (1-\theta) x_i$. A competitive market maker observes q_i and sets the price: $P_i = \lambda_i q_i$, where $\lambda_i > 0$ reflects the stock-specific price impact (Kyle's lambda).

The informed trader chooses β_i to maximize expected profit: $\pi_i = \mathbb{E}[(v_i - P_i) \cdot x_i]$. Substituting the price and order flow expressions yields:

$$\pi_i = (1-\theta)\beta_i \rho_i^2 \sigma_{s,i}^2 (1 - \lambda_i (1-\theta)\beta_i)$$

From the first-order condition, the optimal trading intensity is:

$$\beta_i^* = \frac{1}{2(1-\theta)\lambda_i}$$

The market maker's clearing price must be such that $P_i = \mathbb{E}[v_i | q_i]$. Under normality and linear demand, this implies:

$$\lambda_i = \frac{\mathrm{Cov}(v_i, q_i)}{\mathrm{Var}(q_i)} = \frac{(1-\theta)\beta_i \rho_i \sigma_{v,i}^2}{(1-\theta)^2 \beta_i^2 \rho_i^2 (\sigma_{v,i}^2 + \sigma_{\varepsilon,i}^2) + \theta^2 \sigma_{f,i}^2}$$

Substituting β_i^* into this expression yields the equilibrium price impact:

$$\lambda_i = \frac{1}{2(1-\theta)} \cdot \sqrt{\frac{\rho_i^2 \sigma_{v,i}^2}{\theta^2 \sigma_{f,i}^2 (\sigma_{v,i}^2 + \sigma_{\varepsilon,i}^2)}}$$

Price volatility is given by:

$$\mathrm{Var}(P_i) = \lambda_i^2 \left((1-\theta)^2 \beta_i^2 \rho_i^2 (\sigma_{v,i}^2 + \sigma_{\varepsilon,i}^2) + \theta^2 \sigma_{f,i}^2 \right)$$

Using the equilibrium value of β_i^*, this simplifies to:

$$\text{Var}(P_i) = \frac{1}{4}\rho_i^2(\sigma_{v,i}^2 + \sigma_{\varepsilon,i}^2) + \lambda_i^2\theta^2\sigma_{f,i}^2$$

The informed trader participates only if expected profits exceed the information acquisition cost:

$$\pi_i^* = \frac{1}{2(1-\theta)\lambda_i} \cdot \rho_i^2(\sigma_{v,i}^2 + \sigma_{\varepsilon,i}^2) > c_i$$

If this inequality does not hold, then $\beta_i = 0$, and the market consists solely of passive flows:

$$\text{Var}(P_i) = \lambda_i^2\theta^2\sigma_{f,i}^2$$

This framework yields following testable hypotheses:

H1. Return volatility is increasing in θ (passive share) and in illiquidity λ_i.

H2. Larger or more sophisticated active investors (higher ϕ_i) produce more precise signals (higher ρ_i), leading to smaller volatility.

H3. Informed trading occurs only when market liquidity (low λ_i), active share $(1-\theta)$, and information capacity (ϕ_i) are sufficiently high.

H4. Markets with high passive ownership, low liquidity, and low information capacity are more prone to volatility amplification.

3 Data

3.1 Institutional Investors Ownership

The empirical analysis draws on several comprehensive data sources spanning the period from January 1980 to December 2022. Institutional ownership data are sourced from the Thomson Reuters Institutional Holdings (13F) database (S34), which compiles quarterly institutional holdings from SEC Form 13F filings. Institutional investors are classified into five categories: (1) investment banks, (2) insurance companies, (3) investment companies (including hedge funds), (4) mutual funds families, and (5) pension funds.[1] While Thomson Reuters provides institution-type codes, these are known to contain classification errors starting in December 1998. Therefore, I adopt the corrected institution type classifications from Koijen and Yogo (2019) and Brian Bushee's website. For each institution, I compute dollar holdings in a stock as the product of shares held and stock price, and total assets under management (AUM) as the sum of dollar holdings across all stocks. Following Ben-David, Franzoni, Moussawi, and Sedunov (2021), I identify large institutional investors as those in the top 3, 5, and 10 of the AUM in each quarter and each type based on a rolling four-quarter average.[2]

To separate actively-managed equity funds from aggregate portfolios of mutual fund families, I use the Mutual Fund Holdings database (S12). The Mutual Fund Holdings and Institutional Holdings datasets are closely related and structurally similar, yet they differ in terms of their source data and coverage. The connection between the two arises from the fact that nearly every mutual fund in the S12 dataset is managed by an institution that appears in the S34 dataset. The S34 dataset, derived from SEC Form 13F filings, provides aggregated holdings at the manager or fund family level. For instance, Fidelity (MGRNO=27800) submits a consolidated report that includes the combined holdings of all funds and trusts under its management. At the same time, the S12 dataset contains more granular information on individual mutual funds within the family—such as the

[1]The difference between investment companies and mutual fund families is whether the manager number matches a record in the Mutual Fund Holding database.

[2]Table A1 lists all the institutional investors that enter the top 3 institution ranking in each type during the sample period

Fidelity Magellan Fund (FUNDNO=21858), the firm's largest equity fund—based on disclosures in fund prospectuses and regulatory filings. Following Kacperczyk, Sialm, and Zheng (2008), I identify actively-managed domestic equity funds in the S12 file, and assign MGRNO from the S34 file. Then I aggregate the actively-managed equity funds into the fund family level. Therefore, the manager's new consolidated portfolio does not include any index funds or ETFs.

The main explanatory variable—ownership by large institutions—is computed as the ratio of the aggregate dollar value of holdings in stock i by institutions to the stock's total market capitalization at the end of quarter t:

$$\mathrm{IO}_{it} = \frac{\sum_{j=1}^{J} w_{ijt} AUM_{jt}}{\theta_{it}}$$

where J is the set of institutions that hold stock i, w_{ijt} is the weight of the stock in the portfolio of institution j, AUM_{jt} is assets under management of the institution, and θ_{it} is the market capitalization of the stock.his ownership measure is decomposed into holdings by the top 10 institutions and the remaining institutions and further disaggregated by institutional type for the top 3, 5, and 10. Observations where institutional ownership exceeds 100% are excluded from the analysis to ensure data integrity.

Table 1 reports summary statistics for the top 3 institutions within each of the five main types across subperiods spanning 1980 to 2022. For mutual funds familes, I also separately report statistics for actively managed equity funds. The statistics include the average number of stocks held, average equity assets under management (AUM, in millions of USD), and average portfolio turnover rates, defined as *min(Buys,Sells)/(Average assets* in t and $(t-1)$).

Several patterns emerge from the data. First, mutual funds families have grown to become the dominant institutional investors in terms of both breadth and scale. From 1980–84 to 2020–22, the top 3 mutual fund families increased their average number of holdings from 444 to 4,627 and their average equity AUM from approximately $5.9 billion to over $2.5 trillion. This growth is mirrored by actively managed equity mutual funds, though at a smaller scale, reaching $327 billion in equity assets and over 1,200 holdings by 2020–22.

Second, the data show considerable heterogeneity across institution types in portfolio size and investment concentration. Banks and insurance companies consistently hold large and diversified portfolios—especially in the later years—while pension funds maintain relatively smaller and more concentrated holdings. Notably, pension funds' average AUM remain modest relative to other institutional types.

Third, mutual funds families and investment companies generally exhibit higher turnover rates than banks and pension funds, suggesting more active trading strategies. This is particularly evident in earlier periods (e.g., 1985–89), when investment companies had average turnover rates exceeding 11%, compared to 3–4% for banks and pension funds. Over time, turnover among mutual funds families has declined, likely reflecting the increasing role of passive investment vehicles such as index funds and ETFs within these institutions.

Finally, the sharp growth in mutual fund families AUM, combined with their high breadth of stock coverage and moderately active trading behavior, underscores their central role in shaping modern equity markets. However, the distinction between mutual funds overall and their actively managed subcomponent is critical: while the total mutual fund sector has ballooned in size, the share attributable to actively managed funds is comparatively smaller, which may have implications for understanding their influence on stock return volatility.

3.2 Firm-level Variables

Stock returns, market capitalization, and other firm-level characteristics are obtained from the Center for Research in Security Prices (CRSP) daily and monthly files. The sample is restricted to common stocks listed on major U.S. exchanges (CRSP share codes 10 and 11). The primary dependent variable is stock return volatility, measured as the standard deviation of daily returns within each calendar quarter. This frequency aligns with the availability of institutional ownership data, which is reported quarterly. Firm-level control variables include the logarithm of market capitalization, the inverse of stock price, the Amihud illiquidity ratio, the book-to-market ratio, and cumulative returns over the prior six months. All variables are aggregated to a quarterly frequency to match the temporal resolution of the analysis. To account for heterogeneity in firm size, the sample is further partitioned into microcap and non-microcap stocks, where microcaps are defined as those with market capitalizations below the 20th percentile of NYSE-listed firms in a given quarter.

Table 2 presents descriptive statistics for the variables used in the empirical analysis, based on a panel of 615,726 stock-quarter observations spanning the period from 1980Q1 to 2022Q4. The table includes statistics for the full sample and for two mutually exclusive subsamples: non-microcap and microcap stocks. Microcaps are defined as firms with market capitalizations below the 20th percentile of NYSE-listed stocks in a given quarter.

The full sample reveals substantial heterogeneity in firm size and trading characteristics. The average market capitalization is approximately $3.1 billion, but the distribution is highly right-skewed, with a median of only $181 million and a maximum exceeding $2.9 trillion. Stock return volatility, measured as the standard deviation of daily returns within a quarter, averages 3.42% across the sample. Institutional ownership by 13F filers—defined as the ratio of aggregate institutional holdings to firm market capitalization—has a mean of 39.7%, though it varies widely across firms and over time. Additional firm-level characteristics such as the inverse of stock price, the Amihud illiquidity measure, past six-month returns, and book-to-market ratios all exhibit considerable dispersion, reflecting the diversity of firms in the U.S. equity universe.

The subsample statistics underscore significant differences between microcap and non-microcap firms. Non-microcap stocks are, on average, substantially larger, with a mean market capitalization of $7.04 billion. They also exhibit lower return volatility (2.39%), greater institutional ownership (57.6%), and markedly higher liquidity, as indicated by a mean Amihud illiquidity measure of only 0.143. Their inverse price values are considerably lower, consistent with higher nominal prices, and they tend to show more moderate variation in valuation and momentum indicators.

In contrast, microcap stocks are characterized by extremely small firm size, with an average market capitalization of just $100 million. These firms exhibit substantially higher return volatility (4.22%) and lower institutional ownership (25.8%). They also display pronounced illiquidity, with a mean Amihud measure of 8.331, and a wider range in trading and valuation characteristics. For example, the dispersion in book-to-market ratios and past returns is noticeably greater among microcaps, indicating a more heterogeneous and less efficiently priced segment of the market. The higher values for the inverse price variable further suggest that these firms tend to trade at lower nominal prices, consistent with their limited size and liquidity.

These differences are economically meaningful and methodologically important. Given that microcap stocks represent more than half the cross-section but only a small fraction of total market capitalization (approximately 3%), their influence on unweighted regression estimates can be substantial. The elevated volatility and distinct ownership profiles of microcaps reinforce the need to either analyze them separately or employ market capitalization-weighted approaches to avoid drawing conclusions that may not generalize to the broader market. This distinction plays a central role in the empirical strategy of this paper, particularly in re-evaluating the relationship between large institutional ownership and stock return volatility.

4 Large Institutions' Ownership and Volatility

4.1 Baseline Regression Models

To estimate the effect of ownership by large institutions on volatility, I estimate the following fixed effects regression model following Ben-David et al. (2021):

$$\text{Vol}_{iq} = \beta \cdot \text{TopIO}_{iq-1} + \text{NonTopIO}_{iq-1} + Controls_{iq-1} + \mu_i + \delta_q + \epsilon_{iq} \tag{1}$$

I estimate Equation (1) using standard two-way fixed effects regressions. "TopIO" is the fraction of shares outstanding held by the top 10 institutions, and "NonTopIO" is the fraction held by institutions other than the top 10. *Controls* include log(Market cap), inverse price ratio, Amihud illiquidity ratio, Book-to-market ratio, and past 6-month return. All explanatory variables are lagged by one quarter.

Table 3 presents regression estimates of the effect of large institutions' ownership on stock return volatility, measured as the standard deviation of daily returns at the quarterly frequency. The results are reported for the full sample, a market capitalization-weighted specification, and subsamples of non-microcap and microcap stocks. All specifications include stock and quarter fixed effects, and standard errors are clustered by stock and quarter level.

The first key result pertains to the ownership by the top 10 largest institutional investors. In the full sample, consistent with the result of Ben-David et al. (2021), higher ownership by these institutions is associated with significantly greater volatility, with an estimated coefficient of 0.9202. However, this effect becomes statistically insignificant and economically small in the cap-weighted specification and for non-microcap stocks. In contrast, the effect remains highly significant and nearly doubles in magnitude in the microcap subsample. This finding confirms that the positive relationship between large institutional ownership and volatility is disproportionately driven by microcap stocks, which are more volatile and less liquid. The absence of a significant effect in the non-microcap and cap-weighted models suggests that, for the broader market, large institutional investors do not increase volatility and may even have a neutral or stabilizing effect. The control variables generally behave as expected. Illiquidity (Amihud measure), inverse price, and small market capitalization are all positively associated with higher volatility, consistent with standard asset pricing and market microstructure theories. Notably, the negative coefficient on log market capitalization is particularly large in the microcap sample, highlighting the strong size-volatility relationship.

Collectively, these results provide strong support for the central argument of this paper: the destabilizing effect of large institutional investors, as previously documented in the literature, is largely confined to the microcap segment. Once the sample is stratified or weighted to reflect economic significance by market capitalization, the positive association between large investor ownership and volatility attenuates substantially or disappears altogether. This has important implications for interpreting aggregate market dynamics and for policy concerns related to market stability and the role of institutional ownership.

4.2 Decomposing the Effects of Large Institutions by Type

In this section, I extend the analysis by disaggregating the ownership of the top institutional investors into five types: banks, insurance companies, investment companies (including hedge funds), mutual fund families, and pension funds. I identify the 3 largest institutions in each type, so the total of 15 largest institutions. As before, the regressions are estimated for the full sample, a market capitalization-weighted specification, and separate subsamples of non-microcap and microcap stocks. All models include two-way fixed effects and cluster standard errors at the stock and quarter levels.

The estimates are presented in Table 4. The results reveal substantial heterogeneity in the volatility effects of institutional ownership depending on the type of institution. Among the five groups, investment companies exhibit the most consistent and economically significant negative association with stock return volatility. Across all four specifications, their ownership is strongly associated with lower volatility, with coefficients ranging from –1.40 to –2.41, all significant at the 1% level. These results suggest that large investment companies—many of which may include hedge funds or other active managers—may serve a stabilizing role in the market, potentially due to their research intensity or trading sophistication (Akbas, Armstrong, Sorescu, & Subrahmanyam, 2015).

In contrast, mutual fund families display the opposite pattern. Their ownership is positively and significantly associated with volatility in all specifications. The effect is particularly large in the full sample and cap-weighted models, and remains significant in both non-microcap and microcap subsamples. These findings may align with prior literature documenting that mutual funds may contribute to increase volatility through uninformed flow-driven trading (Coval & Stafford, 2007), or through the propagation of liquidity shocks, especially those managing ETFs (Ben-David, Franzoni, & Moussawi, 2018).

The effect of banks is more nuanced. In the full sample and particularly within the microcap segment, bank ownership is associated with significantly higher volatility. The coefficient for microcaps is the largest among all institution-type effects, suggesting that bank-affiliated institutional investors may introduce instability when operating in the most illiquid parts of the market. However, in the non-microcap sample, the relationship is reversed and significantly negative, indicating that banks may stabilize larger, more liquid stocks. This divergence highlights the importance of disaggregating the market by firm size when analyzing institutional effects.

The results for pension funds are less consistent but broadly suggest a volatility-reducing role in non-microcap stocks. The ownership by the top 3 pension funds is significantly negatively associated with volatility in both the cap-weighted and non-microcap specifications, with particularly large effects in the cap-weighted regression. However, the estimate for microcaps is positive and statistically insignificant, reflecting the more limited role pension funds play in that segment.

Finally, insurance companies do not exhibit statistically significant effects in any of the specifications. This may reflect their conservative investment mandates, lower turnover, or relatively low equity exposure compared to other institutional types. In the appendix, Table A3 and Table A4 do the same anylsis using the top 5 and top 10 institutions in each type, and the results are quantitatively similar.

4.3 Separating Actively Managed Equity Funds from Aggregate Mutual Fund Portfolios

In this section, I investigate whether the previously observed positive relationship between mutual fund ownership and stock return volatility is driven primarily by actively managed equity funds or by other components of large mutual fund families, such as index funds and ETFs. To isolate the effects, this specification replaces the aggregate mutual fund family ownership with a more narrowly defined measure: the ownership share held by the top 3 mutual funds families where the portfolio consists of actively-managed equity funds. The rest of the model structure remains consistent with the prior specification.

The results are shown in Table 5. The most interesting finding is that, once ownership by actively managed equity funds is separated from the broader mutual fund category, the previously positive and significant volatility effects disappear. The coefficient estimates on the ownership by the top 3 mutual funds families with only actively managed funds are positive but statistically insignificant across all subsamples. These results suggest that actively managed equity funds do not significantly contribute to increased stock return volatility, contradicting the interpretation that all mutual fund activity uniformly induces noise in prices. In contrast, the ownership effects for other institutional types remain stable and consistent with earlier results. Investment companies continue to exhibit a robust negative association with volatility across all specifications, with coefficients ranging from –1.42 to –2.43, all significant at the 1% level. Similarly, pension fund ownership is associated with reduced volatility in the full sample, cap-weighted, and non-microcap models, though the effect remains statistically insignificant for microcaps. The coefficient on bank ownership remains large and positive in the microcap segment, and negative in the non-microcap subsample, reinforcing the earlier conclusion that banks exert divergent effects depending on market segment. Insurance companies again display no significant association with volatility, suggesting a more neutral role.

Importantly, the decomposition confirms that the positive volatility effects observed in earlier regressions are not driven by actively managed mutual funds, but rather by other segments within large mutual fund families—most plausibly, ETFs and index funds. This finding aligns with existing literature that documents the volatility-inducing nature of ETFs and raises questions about attributing aggregate effects of mutual funds families to active management alone. In conclusion, these findings highlight the importance of distinguishing among fund types when evaluating the market impact of mutual fund ownership. The lack of a significant effect from actively managed equity funds suggests that regulatory or academic concerns about institutional destabilization should be more carefully directed toward passive vehicles and flow-driven trading structures, rather than active stock-picking strategies.

5 Identification

5.1 Finite Sample Bias

The fixed effects regression can address the omitted-variable bias by accounting for any variation in the volatility due to unobserved time-invariant firm characteristics and common economic shocks in each period. However, adding firm-level fixed effects introduces another finite-sample bias if estimated with OLS. The finite-sample bias is well known as "Stambaugh Bias" in a univariate predictive regression and has been shown to exist in fixed effects estimation (Hjalmarsson, 2010). To remove the finite sample bias, the recursive-demeaning (RD) estimator, first proposed by Moon and Phillips (2000), is commonly used in empirical finance (Pástor et al., 2015; Zhu, 2018). Unlike the previous studies that use the RD estimator in a one-way fixed-effects model, this paper extends the RD estimator in a two-way fixed-effects model. Section 4.2 formally explains why the standard fixed effects estimator suffers from the finite-sample bias, and Section 4.3 shows how to extend the RD estimator in a two-way fixed effects regression model.

5.2 Fixed Effects and Recursive Demeaning

Consider the predictive panel regression model with two-way error components:

$$Y_{it} = X'_{it-1}\beta + \delta_t + u_i + \epsilon_{it} \tag{2}$$

To remove unit and time-fixed effects, the two-way within transformation applied to equation (2) yields

$$Y^*_{it} = X^{*'}_{it-1}\beta + \epsilon^*_{it} \tag{3}$$

where $Y^*_{it} = Y_{it} - \overline{Y}_{i\cdot} - \overline{Y}_{\cdot t} + \overline{Y}_{\cdot\cdot}$, $\overline{Y}_{i\cdot}$ is the time-series average of the unit i, $\overline{Y}_{\cdot t}$ is the cross-section average during time t, and $\overline{Y}_{\cdot\cdot}$ is the full-sample mean. Then the OLS estimator of β is unbiased as long as X^*_{it-1} is uncorrelated with ϵ^*_{it}. However, even though X_{it-1} is uncorrelated with ϵ_{it}, the within transformation makes both X^*_{it-1} and ϵ^*_{it} are functions of the entire time series. Therefore, the OLS estimator is biased if a contemporaneous correlation exists between X_{it} and ϵ_{it}. In our setting, the negative contemporaneous correlation is highly probable because a stock's unexpected high volatility during period t can make institutional investors reduce their holding amounts of the stock. Then the OLS estimator of β in equation (3) is upward biased as shown by Hjalmarsson (2010). More generally, from the perspective of panel data econometrics, this can be understood as the incidental parameter problem when the regressors are weakly exogenous and T is small (Nickell, 1981).

To address the bias in the fixed effects estimator, I employ the RD estimator. First, consider the one-way fixed effects model where δ_t is not included in equation (2). Define the recursively backward-demeaned transformation for $t = 2, ..., T$, as

$$\underline{X}_{it-1} = X_{it-1} - \frac{1}{t-1} \sum_{s=1}^{t-1} X_{is-1}.$$

Similarly, the recursively forward-demeaned transformation for $t = 1, ..., T-1$, is

$$\dot{Y}_{it} = Y_{it} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T} y_{is}$$
$$\dot{X}_{it-1} = X_{it-1} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T} x_{is-1}$$

Applying the recursively forward-demeaned transformation sweeps out the unit fixed effects μ_i:

$$\dot{Y}_{it} = \dot{X}'_{it-1}\beta + \dot{\epsilon}_{it} \tag{4}$$

Pástor et al. (2015) estimate equation (4) using instrumental variable (IV) estimation with $\underline{X}_{it-1}$ as an instrument for $\dot{X}_{it-1}$ because it does not contain information after period $t-1$ and $\dot{\epsilon}_{it}$ only contains information after period t. Zhu (2018) points out the drawback of imposing a zero intercept in Pástor et al. (2015)'s first-stage regression and proposes an enhanced RD estimator by including an intercept and using X_{it-1} as the IV in the first-stage regression. However, it should be noted that the forward-demeaned transformation does not remove the time-fixed effects δ_t. In addition, it is important to highlight that adding time dummies in equation (4) does not filter out the time-fixed effects when the panel is unbalanced. Therefore, I propose a method to extend the Zhu

(2018)'s enhanced RD estimator in the two-way fixed effects model.

5.3 RD Estimator in the Two-way Fixed Effects

To extend the RD estimator in the two-way fixed effects regression, rewrite equation (2) as

$$Y_{it} = X'_{it-1}\beta + \tau_t\delta + u_i + \epsilon_{it} \tag{5}$$

where τ_t is a set of T time dummy variables and $\delta = (\delta_1, ..., \delta_T)'$. Therefore, equation (5) is the dummy variable representation of equation (2). Applying the forward-demeaned transformation to equation (5) yields:

$$\dot{Y}_{it} = \dot{X}'_{it-1}\beta + \dot{\tau}_t\nu + \dot{\epsilon}_{it} \tag{6}$$

To eliminate the time effects, I use a residual regression approach based on the FWL, the Frisch-Waugh-Lovell theorem.[3] First, regress $\dot{Y}_{it}$ on $\dot{\tau}_t$ to obtain a residual $\ddot{Y}_{it}$. Second, regress each regressor of $\dot{X}'_{it-1}$ on $\dot{\tau}_t$ to obtain a residual $\ddot{X}_{it-1}$. Lastly, estimate the residual regression using two-stage least squares following Zhu (2018):

$$\ddot{X}_{it-1} = \alpha + X'_{it-1}\theta + \nu_{it-1} \tag{7}$$

$$\ddot{Y}_{it} = \widehat{\ddot{X}}'_{it-1}\beta + \ddot{\epsilon}_{it} \tag{8}$$

where $\widehat{\ddot{X}}_{it-1}$ is the fitted value from the first-stage regression (7). Note that the FWL theorem tells us that the OLS estimator of β in equation (6) is equivalent to the OLS estimator of the residual regression. However, Giles (1984) shows that the FWL theo-

[3] Directly estimating equation (6) using instrumental variable approach also can be considered. However, as the set of transformed time dummies, $\dot{\tau}_t$, are included regressors, both X_{it-1} and $\dot{\tau}_t$ should be included in the first stage regression. Then we have to deal with many instrumental variables, and 2SLS estimation is likely to perform poorly.

rem also holds for instrumental variable estimation. In addition, X_{it-1} remains a valid instrument for $\ddot{X}_{it-1}$ because residualizing $\dot{Y}_{it}$ with respect to $\dot{\tau}_t$ does not include any information before period $t-1$. Table 6 and Table 7 re-estimate the specifications in Table 4 and Table 5 using the RD procedure. The results from both fixed effects and the RD estimator are similar to each other, and the main findings of this paper still hold even after removing the finite-sample bias.

5.4 A Quasi-Natural Experiment: Mergers Among Institutional Investors

While fixed effects control for time-invariant stock characteristics and common shocks across quarters, they do not fully account for time-varying unobserved confounding factors that may jointly influence both institutional ownership and stock return volatility. In particular, changes in investor behavior, market sentiment, or firm-specific developments may bias the estimated relationship between institutional ownership and volatility if not properly addressed. To strengthen causal inference, this paper employs a quasi-experimental design based on mergers of financial institutions. As noted by He and Huang (2017), the use of institutional mergers as a quasi-experiment relies on the premise that merger decisions are typically unrelated to the fundamentals of the institutions' underlying portfolio holdings. Following a merger, the acquiring institution generally inherits and maintains the target's existing portfolio positions for a sustained period. As a result, when a stock is held by an target institution which is out of the top 10 institutions prior to the merger and an acquiring institution which is the top 10 after the merger, the event induces a plausibly exogenous increase in ownership by large institutions in the immediate post-merger period.

I run the following difference-in-differences regression employing the merger events.[4]

$$\text{Vol}_{iq} = \beta \cdot \text{Treatment}_i \times \text{Postmerger}_q + Controls_{iq-1} + \mu_i + \delta_q + \epsilon_{iq} \tag{9}$$

Table 8 presents the results of a difference-in-differences (DiD) estimation designed to assess the effect of mergers between large and small financial institutions on stock return volatility. The analysis focuses on a symmetric 17-quarter event window spanning from 8 quarters prior to the merger to 8 quarters after. The sample includes stocks held by the acquiring institutions, with a treatment indicator equal to one for those stocks that were previously held by the target institutions and hence likely to be affected by internal portfolio realignment following the merger. The key explanatory variable, Treatment × Postmerger, captures the differential change in return volatility for treated stocks after the merger, relative to non-treated stocks held by the acquirer.

In the equal-weighted specification, the Treatment × Postmerger coefficient is positive and statistically significant at the 10% level , indicating that treated stocks experience an increase in daily return volatility of approximately 6 basis points in the post-merger period relative to control stocks. In contrast, the effect is economically and statistically negligible in the cap-weighted specification, suggesting that this increase in volatility is concentrated in smaller firms. This divergence between the equal- and cap-weighted results is consistent with prior findings in this paper showing that ownership-driven volatility effects are largely confined to microcap or less liquid stocks that are more sensitive to institutional trading behavior.[5]

[4]The lists of mergers used in this analysis are presented in Table A2

[5]Ben-David et al. (2021) similarly analyze the effect of a merger between BlackRock and BGI on volatility and find that volatility increases following by the merger. However, I exclude the merger between BlackRock and BGI because BlackRock acquired iShares from BGI, which is a collection of ETFs and index mutual funds.

6 Conclusion

This paper reexamines the relationship between large institutions' ownership and stock return volatility, a topic of growing relevance given the increasing concentration of equity assets among a small number of large institutional investors. While prior literature has emphasized a positive association between ownership by large institutions and volatility, this paper shows that such effects are not uniform across the market and are largely concentrated in a specific subset of firms and fund types.

By separating the universe of U.S. stocks into microcaps and non-microcaps, I demonstrate that the positive effect of large institutional ownership on volatility is overwhelmingly driven by microcapss that account for more than half of all listed stocks but only a small fraction of total market capitalization. When the analysis is restricted to non-microcaps or employs a market cap-weighted regression, the estimated volatility effect of large institutional investors becomes economically negligible or even reverses in sign. These results suggest that prior findings may overstate the destabilizing role of large institutions from the perspective of aggregate market stability.

Further disaggregation by institutional type reveals considerable heterogeneity in how different types of institutions affect volatility. Investment companies and pension funds are consistently associated with lower stock return volatility, while the positive association observed in aggregate mutual fund ownership is driven entirely by the broader mutual fund family, not actively managed equity funds. Once ETFs and index funds are excluded from the portfolios of mutual fund families, the volatility effect becomes insignificant, pointing to the role of passive and flow-driven vehicles in contributing to market noise.

Taken together, these findings indicate the importance of distinguishing between types of institutions and firm size segments when evaluating the market impact of institutional ownership. While some institutions—especially those managing passive vehicles—may increase volatility in specific market segments, others appear to exert a stabilizing influence. These results have important implications for how researchers, policymakers, and regulators interpret the role of institutional investors in equity market and the design of policies aimed at preserving market stability.

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Table 1: Summary Statistics of Top 3 Institutions Within Each Type

Type	Avg # of stocks held	Avg equity assets ($m)	Avg turnover (%)
1980 - 84			
Banks	1,104	9,158	6.58
Insurance companies	521	6,211	7.29
Investment companies	560	4,946	9.91
Mutual funds families	444	5,886	8.32
Actively-managed equity funds	295	1,212	
Pension funds	227	3,725	3.68
1985 - 89			
Banks	2,946	24,243	3.79
Insurance companies	974	12,105	6.05
Investment companies	1,317	14,065	11.94
Mutual funds families	675	11,120	8.57
Actively-managed equity funds	557	3,965	
Pension funds	1,070	9,733	4.55
1990 - 94			
Banks	3,096	41,060	3.24
Insurance companies	1,431	22,591	5.74
Investment companies	2,390	32,115	5.57
Mutual funds families	1,335	36,691	8.19
Actively-managed equity funds	656	9,864	
Pension funds	1,177	17,693	1.86
1995 - 99			
Banks	4,301	154,469	3.52
Insurance companies	3,665	92,148	7.34
Investment companies	1,934	27,924	3.36
Mutual funds families	1,796	179,066	9.95
Actively-managed equity funds	825	42,682	
Pension funds	1,540	34,549	3.73
2000 - 04			
Banks	4,135	286,571	3.56
Insurance companies	3,502	150,492	6.08
Investment companies	1,274	28,604	5.26
Mutual funds families	2,329	290,284	6.70
Actively-managed equity funds	907	74,923	
Pension funds	1,901	44,662	2.95
2004 - 09			
Banks	4,238	407,900	3.92
Insurance companies	3,523	145,408	8.56
Investment companies	1,698	49,351	11.32
Mutual funds families	2,509	413,912	5.54
Actively-managed equity funds	1,020	137,242	
Pension funds	2,542	47,977	3.59
2010 - 14			
Banks	3,329	368,638	4.27
Insurance companies	2,368	92,651	5.56
Investment companies	2,005	71,305	7.83
Mutual funds families	3,184	723,902	4.20
Actively-managed equity funds	943	147,265	
Pension funds	2,185	43,834	2.13
2014 - 19			
Banks	3,848	611,552	3.94
Insurance companies	2,992	133,351	4.51
Investment companies	2,077	135,946	6.11
Mutual funds families	3,827	1,533,534	2.79
Actively-managed equity funds	1,065	224,415	
Pension funds	2,357	65,549	4.11
2020 - 22			
Banks	4,578	923,387	2.98
Insurance companies	3,232	219,341	4.25
Investment companies	2,283	221,771	6.06
Mutual funds families	4,627	2,565,905	2.68
Actively-managed equity funds	1,216	327,379	
Pension funds	2,300	90,735	3.87

Table 2: Summary Statistics

	N	Mean	Std.Dev	Min	p25	Median	p75	Max
All Samples								
Market Cap ($m)	615,726	3,141	22,869	0.04	41	181	918	2,902,368
Daily Volatility (%)	615,726	3.416	2.447	0.000	1.794	2.712	4.222	23.889
Ownership by 13F institutions	615,726	0.397	0.296	0.000	0.124	0.354	0.647	1.000
1/Price	615,726	0.245	0.635	0.000	0.041	0.086	0.207	12.800
Amihud illiquidity	615,726	4.745	25.913	0.000	0.004	0.058	0.922	1085.164
log(Market cap)	615,726	5.333	2.211	-0.942	3.719	5.199	6.823	12.172
Past 6-month return	615,726	0.070	0.424	-0.933	-0.159	0.029	0.223	6.258
Book-to-market	615,726	0.758	0.725	-2.809	0.327	0.607	0.991	8.986
Non-Microcaps								
Market Cap ($m)	269,692	7,044	34,162	46	457	1180	3640	2,902,368
Daily Volatility (%)	269,692	2.385	1.392	0.000	1.476	2.022	2.878	21.531
Ownership by 13F institutions	269,692	0.576	0.259	0.000	0.376	0.602	0.796	1.000
1/Price	269,692	0.088	0.206	0.000	0.027	0.047	0.084	12.800
Amihud illiquidity	269,692	0.143	1.262	0.000	0.001	0.004	0.030	239.265
log(Market cap)	269,692	7.247	1.521	3.826	6.125	7.073	8.198	12.172
Past 6-month return	269,692	0.113	0.360	-0.933	-0.077	0.074	0.240	6.258
Book-to-market	269,692	0.610	0.496	-2.809	0.291	0.510	0.817	8.986
Microcaps								
Market Cap ($m)	346,034	100	132	0.04	19	50	123	1,026
Daily Volatility (%)	346,034	4.219	2.770	0.000	2.343	3.502	5.254	23.889
Ownership by 13F institutions	346,034	0.258	0.243	0.000	0.060	0.178	0.397	1.000
1/Price	346,034	0.367	0.807	0.000	0.073	0.150	0.334	12.800
Amihud illiquidity	346,034	8.331	34.119	0.000	0.056	0.515	3.533	1085.164
log(Market cap)	346,034	3.842	1.347	-0.942	2.937	3.911	4.812	6.935
Past 6-month return	346,034	0.037	0.465	-0.933	-0.231	-0.016	0.205	6.258
Book-to-market	346,034	0.874	0.845	-2.809	0.375	0.704	1.139	8.986

Notes. This table presents summary statistics for key variables used in the analysis. The sample period is 1980 Q1 - 2022 Q4

Table 3: Aggregate effects of large institutions on volatility

Dependent Variable:	Standard deviation of daily returns (q; %)			
Model:	All Samples	Cap-weighted	Non-microcaps	Microcaps
Variables				
Ownership by top 10 largest investors (q-1)	0.9202***	0.1410	-0.1359	1.665***
	(0.1235)	(0.1228)	(0.0924)	(0.2113)
Ownership by all but top 10 investors (q-1)	-0.4143***	-0.5278***	-0.4783***	0.1676*
	(0.0578)	(0.0940)	(0.0552)	(0.0914)
1/Price (q-1)	0.3192***	0.5024***	0.1574***	0.2565***
	(0.0625)	(0.1259)	(0.0401)	(0.0651)
Amihud illiquidity (q-1)	0.0138***	0.0147***	0.0014	0.0123***
	(0.0015)	(0.0019)	(0.0055)	(0.0013)
log(Market cap) (q-1)	-0.5564***	-0.1602***	-0.2006***	-0.8965***
	(0.0270)	(0.0348)	(0.0285)	(0.0355)
Book-to-market (q-1)	0.0060	0.0982**	0.0225	-0.0503**
	(0.0195)	(0.0426)	(0.0217)	(0.0211)
Past 6-month return (q-3 to q-1)	-0.1412*	0.0242	0.0260	-0.1419**
	(0.0758)	(0.0998)	(0.0692)	(0.0628)
Fixed-effects				
PERMNO	Yes	Yes	Yes	Yes
qdate	Yes	Yes	Yes	Yes
Fit statistics				
Observations	615,726	615,726	269,692	346,034
R^2	0.65098	0.69516	0.65776	0.61981
Within R^2	0.15807	0.02448	0.02588	0.17693

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Decomposing the effects by institution types

Dependent Variable:	Standard deviation of daily returns (q; %)			
Model:	All Samples	Cap-weighted	Non-microcaps	Microcaps
Variables				
Ownership by top 3 banks (q-1)	2.539***	-0.4350	-0.7731***	7.498***
	(0.3804)	(0.3447)	(0.2334)	(0.8556)
Ownership by top 3 insurance companies (q-1)	-0.4039	0.3840	-0.1545	-0.4402
	(0.2762)	(0.4126)	(0.2351)	(0.5140)
Ownership by top 3 investment companies (q-1)	-1.693***	-1.691***	-1.403***	-2.414***
	(0.3451)	(0.5364)	(0.2663)	(0.6706)
Ownership by top 3 mutual funds families (q-1)	1.090***	0.6727***	0.4153***	0.8388***
	(0.1854)	(0.1988)	(0.1382)	(0.3084)
Ownership by top 3 pension funds (q-1)	-1.800**	-4.858***	-2.249***	2.508
	(0.9021)	(1.043)	(0.5657)	(1.950)
Ownership by all but top investors (q-1)	-0.4196***	-0.4421***	-0.4508***	0.0571
	(0.0564)	(0.0921)	(0.0542)	(0.0895)
1/Price (q-1)	0.3181***	0.5088***	0.1587***	0.2515***
	(0.0626)	(0.1213)	(0.0402)	(0.0649)
Amihud illiquidity (q-1)	0.0138***	0.0144***	0.0008	0.0122***
	(0.0014)	(0.0018)	(0.0055)	(0.0013)
log(Market cap) (q-1)	-0.5584***	-0.1561***	-0.1979***	-0.9163***
	(0.0271)	(0.0342)	(0.0282)	(0.0358)
Book-to-market (q-1)	0.0055	0.0925**	0.0221	-0.0508**
	(0.0195)	(0.0422)	(0.0216)	(0.0213)
Past 6-month return (q-3 to q-1)	-0.1406*	0.0180	0.0206	-0.1286**
	(0.0757)	(0.0998)	(0.0692)	(0.0624)
Fixed-effects				
PERMNO	Yes	Yes	Yes	Yes
qdate	Yes	Yes	Yes	Yes
Fit statistics				
Observations	615,726	615,726	269,692	346,034
R^2	0.65132	0.69570	0.65826	0.62080
Within R^2	0.15889	0.02620	0.02728	0.17906

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Separating actively-managed equity funds from aggregate portfolio of mutual funds families

Dependent Variable:	Standard deviation of daily returns (q; %)			
Model:	All Samples	Cap-weighted	Non-microcaps	Microcaps
Variables				
Ownership by top 3 banks (q-1)	2.835***	-0.2473	-0.6930***	7.691***
	(0.3848)	(0.3453)	(0.2307)	(0.8524)
Ownership by top 3 insurance companies (q-1)	-0.3993	0.4491	-0.1344	-0.4462
	(0.2758)	(0.4143)	(0.2354)	(0.5137)
Ownership by top 3 investment companies (q-1)	-1.745***	-1.703***	-1.416***	-2.429***
	(0.3475)	(0.5374)	(0.2672)	(0.6774)
Ownership by top 3 active mutual funds (q-1)	0.3875	0.0978	0.0742	0.2273
	(0.2515)	(0.1060)	(0.0965)	(0.4177)
Ownership by top 3 pension funds (q-1)	-1.944**	-4.605***	-2.222***	2.613
	(0.8991)	(1.045)	(0.5653)	(1.955)
Ownership by all but top investors (q-1)	-0.4050***	-0.4136***	-0.4429***	0.0784
	(0.0566)	(0.0912)	(0.0545)	(0.0895)
1/Price (q-1)	0.3209***	0.5108***	0.1595***	0.2527***
	(0.0628)	(0.1222)	(0.0402)	(0.0650)
Amihud illiquidity (q-1)	0.0138***	0.0145***	0.0010	0.0122***
	(0.0014)	(0.0018)	(0.0055)	(0.0013)
log(Market cap) (q-1)	-0.5477***	-0.1547***	-0.1961***	-0.9102***
	(0.0268)	(0.0345)	(0.0286)	(0.0356)
Book-to-market (q-1)	0.0074	0.0936**	0.0228	-0.0499**
	(0.0196)	(0.0421)	(0.0216)	(0.0214)
Past 6-month return (q-3 to q-1)	-0.1444*	0.0216	0.0211	-0.1319**
	(0.0759)	(0.0996)	(0.0692)	(0.0624)
Fixed-effects				
PERMNO	Yes	Yes	Yes	Yes
qdate	Yes	Yes	Yes	Yes
Fit statistics				
Observations	615,726	615,726	269,692	346,034
R^2	0.65113	0.69542	0.65815	0.62074
Within R^2	0.15844	0.02532	0.02698	0.17894

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Recursive Demeaning Estimation by Institution Types

Dependent Variable:	Standard deviation of daily returns (q; %)		
Model:	All Samples	Non-microcaps	Microcaps
Variables			
Ownership by top 3 banks (q-1)	0.8052	-1.282***	7.560***
	(0.7549)	(0.4324)	(1.338)
Ownership by top 3 insurance companies (q-1)	-1.085**	-0.3710	-1.975*
	(0.5410)	(0.5455)	(1.060)
Ownership by top 3 investment companies (q-1)	-2.220***	-1.916***	-1.368
	(0.6568)	(0.3726)	(1.154)
Ownership by top 3 mutual funds families (q-1)	0.7743*	1.222***	1.629**
	(0.4370)	(0.3347)	(0.7254)
Ownership by top 3 pension funds (q-1)	2.356	-1.149	8.329**
	(1.743)	(0.9165)	(3.624)
Ownership by all but top investors (q-1)	-0.2046	-0.2024*	0.1139
	(0.1684)	(0.1198)	(0.2491)
log(Market cap) (q-1)	-0.8453***	-0.3111***	-0.9064***
	(0.2100)	(0.0664)	(0.1199)
1/Price (q-1)	0.0664	0.0486	0.7922***
	(0.2046)	(0.0780)	(0.1476)
Amihud illiquidity (q-1)	0.0119***	-0.0040	0.0085***
	(0.0013)	(0.0053)	(0.0015)
Book-to-market (q-1)	-0.0219	-0.0889*	-0.0832*
	(0.0486)	(0.0488)	(0.0493)
Past 6-month return (q-3 to q-1)	0.0447	0.1021	0.0273
	(0.0571)	(0.0776)	(0.0497)
Fit statistics			
Observations	598,795	261,402	332,220
R^2	0.02020	0.00848	0.02367

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Recursive Demeaning Estimation by Institution Types

Dependent Variable:	Standard deviation of daily returns (q; %)		
Model:	All Samples	Non-microcaps	Microcaps
Variables			
Ownership by top 3 banks (q-1)	0.9133	-1.357***	7.776***
	(0.7433)	(0.4542)	(1.362)
Ownership by top 3 insurance companies (q-1)	-1.183**	-0.4005	-2.078**
	(0.5366)	(0.5288)	(1.045)
Ownership by top 3 investment companies (q-1)	-2.364***	-1.969***	-1.365
	(0.6610)	(0.3652)	(1.178)
Ownership by top 3 active mutual funds (q-1)	-0.0194	0.1514	-0.7152
	(0.2306)	(0.2269)	(0.7559)
Ownership by top 3 pension funds (q-1)	1.830	-1.560	8.554**
	(1.792)	(0.9453)	(3.650)
Ownership by all but top investors (q-1)	-0.2139	-0.2245*	0.0813
	(0.1665)	(0.1145)	(0.2470)
log(Market cap) (q-1)	-0.8337***	-0.2555***	-0.9252***
	(0.2175)	(0.0660)	(0.1175)
1/Price (q-1)	0.0600	0.1009	0.7574***
	(0.2099)	(0.0758)	(0.1476)
Amihud illiquidity (q-1)	0.0120***	-0.0029	0.0086***
	(0.0013)	(0.0053)	(0.0015)
Book-to-market (q-1)	-0.0169	-0.0815*	-0.0777
	(0.0491)	(0.0485)	(0.0494)
Past 6-month return (q-3 to q-1)	0.0399	0.0999	0.0212
	(0.0576)	(0.0776)	(0.0500)
Fit statistics			
Observations	598,795	261,402	332,220
R^2	0.02020	0.00848	0.02367

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Volatility around mergers of financial institutions

Dependent Variable:	Standard deviation of daily returns (q; %)	
Event window:	(-8, +8) quarters	
Model:	Equal-weighted	Cap-weighted
Variables		
Treatment x Postmerger	0.0619*	0.0057
	(0.0349)	(0.0353)
Ownership by all institutions (q-1)	-0.0797	-0.1806
	(0.1147)	(0.1239)
1/Price (q-1)	0.9804***	1.143***
	(0.1337)	(0.2155)
Amihud illiquidity (q-1)	0.0170***	0.0246***
	(0.0027)	(0.0048)
log(Market cap) (q-1)	-0.3919***	-0.0226
	(0.0488)	(0.0597)
Book-to-market (q-1)	-0.0423	-0.0058
	(0.0312)	(0.0503)
Past 6-month return (q-3 to q-1)	-0.0186	0.1731*
	(0.0873)	(0.1011)
Fixed-effects		
PERMNO	Yes	Yes
qdate	Yes	Yes
Fit statistics		
Observations	102,523	102,523
R^2	0.72981	0.75672
Within R^2	0.09511	0.01553

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

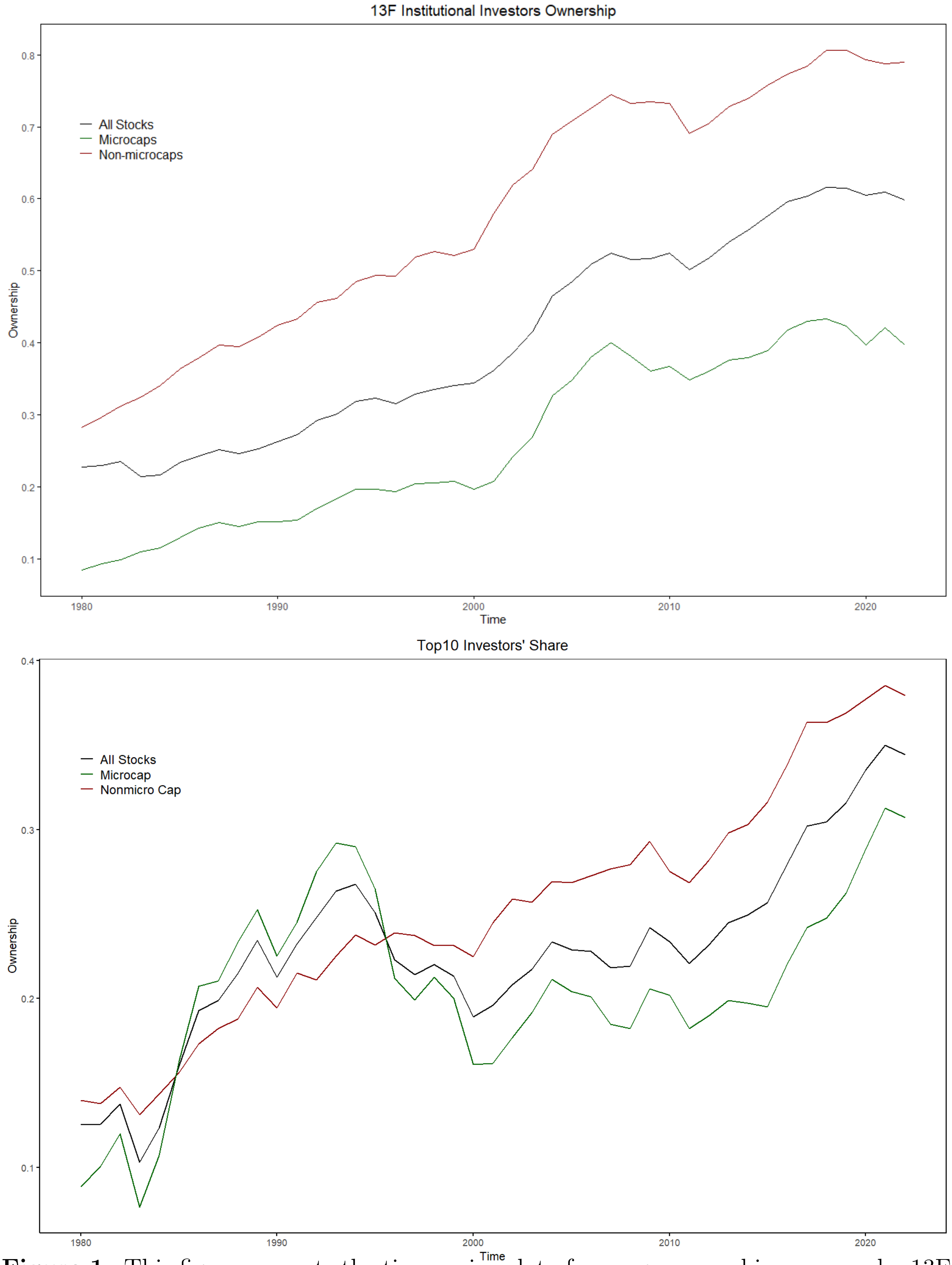

Figure 1: This figure presents the time-series plot of average ownership measure by 13F institutional investors in each cross-section over the sample period between 1980Q1 and 2022Q4. The ownership measure is the sum of shares owned by institutional investors, divided by total shares outstanding. The sample in the upper panel includes ownership by all 13F investors and the sample in the lower panel includes ownership by top 10 investors. The black line is for all stocks, the red for non-microcaps, and the green for microcaps.

Table A1: Top 3 Institutional Investors in Each Type

13F institution name	Mgrno	First quarter	Last quarter	Avg # of stocks held	Avg equity assets ($m)
Banks					
Morgan J P & Co Inc	58835	1980-03-31	2022-12-31	2868	261334
Citicorp	16260	1980-03-31	1983-09-30	815	7101
Bankers Tr New York Corp (Deutsche Bk)	7800	1980-03-31	2004-12-31	3222	65714
First Interstate Bancorp	29800	1982-12-31	1984-03-31	1880	7872
Mellon Bank Corporation	55390	1983-09-30	2017-03-31	3790	145718
Wells Fargo Bank N.A.	92035	1983-12-31	1990-09-30	3231	25452
State Street Boston Corp	81540	1990-12-31	2022-12-31	3210	574336
Barclays Bank Plc	7900	1996-09-30	2009-09-30	5079	436395
Northern Trust Corp	65260	2008-12-31	2022-12-31	4299	381432
Insurance companies					
Prudential Ins Co/Amer	72280	1980-03-31	1994-09-30	1084	9716
College Retirement Eq Fd (TIAA)	18265	1980-03-31	2022-12-31	2373	78957
Equitable Life Assur (Axa)	25610	1980-03-31	2022-12-31	2872	138836
State Farm Mut Automobile Ins	81120	1985-09-30	2003-12-31	201	9787
Travelers Inc (Citigroup Inc)	84900	1994-12-31	2009-12-31	3991	103886
Legal & General Group Plc	50100	2010-03-31	2022-12-31	2465	131222
Investment companies					
Fayez Sarofim & Co	76045	1980-03-31	2006-09-30	240	19982
Edie Lionel D & Co	24480	1980-03-31	1981-09-30	445	3197
Fmr Corp	26590	1980-03-31	1990-12-31	1717	15708
Donaldson Lufkin& Jenrett	23375	1980-12-31	1986-03-31	679	6949
Eberstadt Asset Mgmt Inc	24440	1982-06-30	1982-12-31	165	2363
Alliance Capital Mgmt	1250	1986-03-31	1993-06-30	1740	19642
Neuberger & Berman	63050	1986-09-30	2017-06-30	1424	55755
Merrill Lynch Asset Mgmt	56800	1988-03-31	1993-12-31	806	10683
Shearson Lehman Brothers	78685	1988-06-30	1989-06-30	1171	7841
Bzw Barclays Glbl Invts	92040	1990-06-30	1996-03-31	5293	70470
Boston Company Inc	9750	1993-09-30	1993-09-30	1860	15103
Neuberger & Berm Inst Asst	63065	1994-03-31	1996-09-30	802	6413
World Asset Management	93830	1995-06-30	2001-09-30	3529	14204
Hartford Invt Finl Svcs	43900	1996-12-31	1998-12-31	563	14274
Gabelli Asset Management Co	39580	2001-12-31	2004-06-30	1016	16696
Goldman Sachs Asset Mgmt (US)	7871	2003-03-31	2003-03-31	2635	45572
Fund Asset Management	39537	2004-09-30	2005-06-30	3722	25670
D. E. Shaw & Co., L.p.	78600	2005-09-30	2007-09-30	1979	37798
Blackrock Advisors, Llc	11386	2006-12-31	2017-03-31	2833	72007
Renaissance Technologies Corp.	73460	2007-03-31	2020-09-30	3236	74646
Clearbridge Advr	12058	2008-06-30	2022-09-30	982	83782
Managed Acct Advr Llc	11697	2012-03-31	2022-12-31	2882	207960
Janus Henderson Investors	44450	2017-09-30	2022-12-31	1621	181630
Lpl Financial	11641	2022-12-31	2022-12-31	4371	116478
Mutual Funds Families					
Price T Rowe Associates	71110	1980-03-31	1983-09-30	398	5467
Putnam Management	72400	1980-03-31	2001-12-31	1180	101018
Batterymarch Fin Mgmt	8190	1980-03-31	1986-12-31	738	7204
State Street Resrch& Mgmt	81575	1980-09-30	1986-03-31	248	6516
Wellington Management Co	91910	1984-09-30	1995-12-31	1278	19005
Capital Guardian Trust	12480	1985-06-30	1985-06-30	342	6284
Delaware Management Co	22620	1986-03-31	1990-12-31	352	11357
Capital Research & Mgmt	12740	1987-03-31	2007-09-30	612	150866
Fidelity Management & Research	27800	1991-03-31	2022-12-31	2975	504151
Vanguard Group	90457	2000-06-30	2022-12-31	3937	1267337
Janus Capital Corporation	48170	2000-09-30	2000-12-31	469	182067
Capital World Investors	11836	2007-12-31	2010-06-30	512	250621
Blackrock Inc	9385	2010-09-30	2022-12-31	4489	1825753
Pension Funds					
U S Steel&Carnegie Pen	89180	1980-03-31	1985-06-30	236	3894
N.Y. State Teach' Retire Sys	63895	1980-03-31	2014-03-31	1080	22586
Dupont De Nemours + Co	23920	1980-03-31	1986-09-30	319	4410
California Publ Emp Retm	12090	1980-06-30	1987-03-31	384	5930
G E Pension Trust	40510	1980-09-30	1986-09-30	352	3979
American Tel & Tel Index	3650	1986-03-31	1986-03-31	836	6404
New York State Common Retireme	63850	1986-12-31	2022-12-31	1873	46974
General Elec Master Retr	40504	1987-03-31	1987-09-30	707	6768
Texas Teacher Retirm Sys	83360	1987-09-30	2007-12-31	1516	40548
California State Teach Retire	12120	1987-12-31	2022-12-31	3561	22548
California Public Emp Ret Sys	12000	1988-12-31	2022-12-31	2640	52558
Michigan Dept Of Treasury	57500	1999-03-31	1999-03-31	927	22266
The State Teach Retire Sys Oh	66635	1999-03-31	1999-03-31	1441	19999
Florida State Bd Administratio	38330	2010-03-31	2010-06-30	2608	31906
Algemeen Burgerlijk Pensioenf.	10670	2014-06-30	2021-03-31	790	56138
Canada Pens Plan Investment Bd	11449	2021-09-30	2022-09-30	1317	74853

Notes. The list of the top 3 institutional investors in each type

Table A2: Lists of financial institution mergers used in the analysis

Effective date	Acquirer	Target	Acquirer mgrno	Target mgrno	Pre-merger acquirer rank	Post-merger acquirer rank	Pre-merger target rank
1984-07-01	Chase Manhattan Corp	Lincoln 1st Banks Inc	15230	51220	8	8	33
1986-07-15	First Interstate Bancorp	First Natl Bk & Tr	29800	36140	4	4	98
1987-02-27	PNC Financial	Citizens Fidelity BK & TR	67600	16575	8	8	79
1989-03-31	PNC Financial	Bank of Delaware	67600	6500	8	8	94
1992-07-23	PNC Financial	First National Bank Pennsylvania	67600	34640	9	9	168
1994-08-15	Banc One Corp	Liberty National Bancorp	5955	50680	10	8	82
1996-03-31	Chemical Banking Corp	Chase Manhattan Corp	15345	15230	14	10	20
1996-12-12	First Union Corp	Keystone Investments Inc	37700	49250	13	10	71
1997-01-06	NationsBank Corp	Boatmen's Bancshares	62890	9480	9	7	14
1998-04-01	Mellon Bank Corp	Founders Asset Management Inc	55390	38870	4	3	112
1998-09-30	NationsBank Corp	BankAmerica Corp	62890	5980	6	7	16
1998-12-31	SunTrust Banks Inc	Crestar Finl Corp	82355	21650	7	9	42
1998-10-08	Travelers Group Inc	Citicorp	84900	16260	2	2	21
2000-10-02	Axa Financial, Inc	Sanford C Bernstein & Co Inc	25610	8650	1	1	19
2004-07-01	JPMorgan Chase & Co	Bank One Corp	58835	5955	6	6	12
2005-01-03	Wells Fargo & Co	Strong Financial-Fund Asts	65850	82100	9	9	60
2005-08-04	Transamerica Investment Mgmt	Westcap Investors LLC	84750	92160	8	9	58
2009-12-01	Blackrock Inc	Barclays Global Fund Advisors	9385	7900	84	1	1
2010-04-06	Goldman Sachs Group Inc	Level Global Investors LP	41260	10194	8	9	101

Table A3: Decomposing the effects by institution types (top 5)

Dependent Variable:	Standard deviation of daily returns (q; %)			
Model:	All Samples	Cap-weighted	Non-microcaps	Microcaps
Variables				
Ownership by top 5 banks	1.932***	-0.5243*	-0.7943***	5.605***
	(0.2994)	(0.3132)	(0.2046)	(0.6361)
Ownership by top 5 insurance companies	-0.7266***	-0.1342	-0.4464**	-0.3301
	(0.2467)	(0.3523)	(0.1997)	(0.4403)
Ownership by top 5 investment companies	-1.682***	-1.533***	-1.155***	-2.292***
	(0.2999)	(0.4688)	(0.2282)	(0.5312)
Ownership by top 5 mutual funds	0.9030***	0.4478***	0.1462	0.8740***
	(0.1512)	(0.1490)	(0.1053)	(0.2400)
Ownership by top 5 pension funds	-1.607***	-3.519***	-1.690***	1.367
	(0.4862)	(0.6445)	(0.3693)	(0.9051)
Ownership by all but top investors (q-1)	-0.4340***	-0.4157***	-0.4091***	0.0246
	(0.0575)	(0.0900)	(0.0557)	(0.0902)
1/Price (q-1)	0.3175***	0.5071***	0.1581***	0.2518***
	(0.0626)	(0.1215)	(0.0402)	(0.0649)
Amihud illiquidity (q-1)	0.0138***	0.0144***	0.0009	0.0122***
	(0.0014)	(0.0018)	(0.0055)	(0.0013)
log(Market cap) (q-1)	-0.5588***	-0.1564***	-0.1989***	-0.9119***
	(0.0271)	(0.0345)	(0.0284)	(0.0356)
Book-to-market (q-1)	0.0070	0.0946**	0.0232	-0.0481**
	(0.0195)	(0.0420)	(0.0216)	(0.0212)
Past 6-month return (q-3 to q-1)	-0.1399*	0.0174	0.0201	-0.1299**
	(0.0757)	(0.0997)	(0.0692)	(0.0624)
Fixed-effects				
PERMNO	Yes	Yes	Yes	Yes
qdate	Yes	Yes	Yes	Yes
Fit statistics				
Observations	615,726	615,726	269,692	346,034
R^2	0.65136	0.69559	0.65808	0.62078
Within R^2	0.15901	0.02588	0.02677	0.17903

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: Decomposing the effects by institution types (top 10)

Dependent Variable:	Standard deviation of daily returns (q; %)			
Model:	All Samples	Cap-weighted	Non-microcaps	Microcaps
Variables				
Ownership by top 10 banks	1.418***	-0.6007**	-0.7259***	3.748***
	(0.2193)	(0.2686)	(0.1527)	(0.4330)
Ownership by top 10 insurance companies	-0.4657**	0.0304	-0.3911**	0.2507
	(0.2074)	(0.3445)	(0.1700)	(0.4094)
Ownership by top 10 investment companies	-1.475***	-1.447***	-1.030***	-1.411***
	(0.2341)	(0.3693)	(0.1861)	(0.4162)
Ownership by top 10 mutual funds	1.037***	0.4085***	0.2372**	1.102***
	(0.1301)	(0.1253)	(0.0956)	(0.2044)
Ownership by top 10 pension funds	-1.117***	-1.475***	-1.131***	1.352**
	(0.3525)	(0.5354)	(0.2776)	(0.6697)
Ownership by all but top investors (q-1)	-0.5882***	-0.5199***	-0.4832***	-0.0792
	(0.0634)	(0.1013)	(0.0621)	(0.0943)
1/Price (q-1)	0.3151***	0.5005***	0.1578***	0.2531***
	(0.0624)	(0.1219)	(0.0402)	(0.0649)
Amihud illiquidity (q-1)	0.0137***	0.0144***	0.0006	0.0122***
	(0.0014)	(0.0018)	(0.0055)	(0.0013)
log(Market cap) (q-1)	-0.5648***	-0.1619***	-0.2039***	-0.9053***
	(0.0268)	(0.0344)	(0.0281)	(0.0353)
Book-to-market (q-1)	0.0060	0.0950**	0.0230	-0.0498**
	(0.0195)	(0.0424)	(0.0217)	(0.0212)
Past 6-month return (q-3 to q-1)	-0.1355*	0.0177	0.0230	-0.1323**
	(0.0758)	(0.0996)	(0.0693)	(0.0625)
Fixed-effects				
PERMNO	Yes	Yes	Yes	Yes
qdate	Yes	Yes	Yes	Yes
Fit statistics				
Observations	615,726	615,726	269,692	346,034
R^2	0.65167	0.69575	0.65831	0.62059
Within R^2	0.15975	0.02636	0.02742	0.17861

Clustered (PERMNO & qdate) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*