Institutional segmentation in equity markets

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Abstract

A stock's capacity to facilitate investment (i.e., market capitalization, trading volume) induces segmentation in institutional investment. Scale diseconomies relating to implementation costs are an obvious explanation, but our evidence points to an important role for contracting considerations – monitoring and agency conflict. Consistent with this, we find increased segmentation with: (1) Small institutions with insufficient reputational capital to alleviate agency concerns, who must restrict investment to 'safe' stocks. (2) Institution categories prone to due-diligence concerns. (3) Clienteles with inefficient (redundant) monitoring (e.g, separate accounts) rather than efficient monitoring (e.g., pooled investment vehicles). (4) Low information-production capacity (implying higher adverse selection concerns).

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1. Introduction

Many studies refer to patterns in institutional ownership (IO) that identify preferences. We investigate the extent to which it is meaningfully to extrapolate these patterns to a view of market segmentation in institutional ownership. The distinction is relevant on several counts. First, segmentation is a natural implication of combining portfolio implementation costs with fixed costs of information production and investment due diligence. Second, segmentation provides a foundation for asset pricing effects. Third, segmentation (at least, if exogenously derived) motivates an investigation of institutional performance using 'fair' return benchmarks based on feasible factors. Our study considers each of these dimensions.

The literature finds that many stock characteristics predict institutional ownership, but none carry a more central position than the *capacity* of a stock's market to accommodate institutional ownership and trading (i.e., capitalization and trading activity). Capacity underlies the conventional wisdom that scale diseconomies in investment management relate to transaction costs. The seminal reference on scale diseconomies is Berk and Green (2004), who outline the premise and study its equilibrium implications. This premise is given empirical support in Edelen et al. (2013) and it follows a simple logic. Information asymmetry and supply / inventory considerations imply downward-sloping aggregate demand for individual stocks —particularly in the short run. Thus, when a relatively large institution seeks to implement a position change, it can expect a relatively large price impact.

As a result, a pre-trade information advantage of a given amount (i.e., a "paper portfolio") is less relevant for larger institutions, since their post-trade portfolio return (and therefore performance as an investment manager) is net of implementation costs. This implies scale diseconomies. But it also implies segmentation in institutional investment driven by scale. A stock with limited capacity to accommodate an institution's demand to hold (and trade) an investment position is arguably not worthy of ex ante consideration (Merton, 1987). This follows on both informational and due diligence (prudence) grounds, both of which imply a fixed cost of consideration. If the institution cannot cost-effectively acquire a sufficiently large position to offset these fixed costs, then the institution will avoid the stock. That avoidance should be more likely the larger the institutions' trading demands, ceteris paribus, giving us a scaled-driven segmentation hypothesis. Indeed, stocks with limited capacity (i.e., small capitalization and low trading volume) should offer smaller institutions a safe haven from competition, giving them a comparative advantage. This both underlies the Berk and Green (2004) model and implies that smaller institutions should be more inclined to hold small stocks, further suggesting that institutional segmentation should be driven by scale.

Our study tests this hypothesis of scale-driven segmentation in institutional ownership on two levels. We first seek to identify segmentation using a variety of determinants of institutional ownership found to have significance in the literature. Motivated by the above logic, we first consider capacity variables. These are market capitalization and trading volume, scaled to the concurrent median institution size. We also consider a category of stock characteristics that relate to market statistics (like past returns and volatility); and a category of stock characteristics that relate to firm fundamentals (like Market to book or return on assets). Our final category of stock characteristics is index indicators. Consistent with the literature (e.g., Gompers and Metrick, 2001; Lewellen, 2011) we find that these other considerations provide substantial incremental improvement beyond capacity in predicting IO, using a linear specification. Noteworthy, most of the incremental explanatory power comes from the index indicators, which are obviously relevant to segmentation (e.g. passive portfolios).

However, when we consider an expanded specification that accommodates segmentation (more specifically, the S-shaped logistic function) we find two key results. First, a specification that accounts for segmentation effects substantially improves the explanatory power of IO. Indeed, using just capacity determinants, we find that the R-squared rises from 73% to 92%. Second, capacity determinants are essentially all that is needed to explain IO, provided the specification accommodates segmentation. That is, market capitalization and trading volume almost completely subsume the explanatory power of all other IO determinants found in the literature, combined. We conclude that segmentation is a critical feature of institutional ownership and that its origin aligns with the above development of the scale-driven segmentation hypothesis. Overall, this evidence supports Merton (1987).

We then turn to a more direct examination of the scale-driven segmentation hypothesis. Its most direct prediction is a positive relation between institution size and segmentation tendencies. We find surprisingly contrary evidence on this prediction. While all quintiles of institutions ranked by equity under management (EUM) exhibit segmentation tendencies, those in the larger quintiles (particularly the largest) exhibit the least segmentaiton tendencies. That is, larger institutions are more likely to invest in low-capacity stocks than smaller institutions. Overall, the equity capital provided to smaller firms comes primarily from larger institutions. Put another way, we find little support for the conventional wisdom that small institutions exploit a competitive advantage in implementation costs by specializing in low capacity stocks. They tend to focus on larger capitalization stocks – more so than large institutions.

We argue that this may not be so surprising from a contracting perspective. In the above argument, fixed costs of due diligence and information production underlie institutional segmentation. Further, *scale-driven* segmentation is based on a ceteris paribus that holds all else constant while implementation costs expand. But an institutions' task of convincing investors and regulators that they have conducted sufficient diligence in evaluating the prudence and soundness of investment is not likely constant across institutions.

We outline three dimensions that might generate variation in the difficulty of achieving due diligence across institutions. Each implies variation in segmentation independent of, or contrary to, scale-driven segmentation. These are: (1) *Decreasing* segmentation with institution size, as size proxies for the institution's internal incentive to "do the right thing" to preserve reputational capital (the cost of a flagrant due diligence violation is far higher for a large firm). (2) Segmentation relating to the category of institution, as the cost of due-diligence violations is likely more severe at some types than others (see e.g. Del Guercio, 1996). (3) The nature of the clientele (individuals versus pooled investment vehicles).

Using the 13f data and Form ADV filings we find support for thee alternatives to the scale-driven segmentation hypothesis. First, using a variety of analyses (Table 2 and Figure 5), we find that ownership of smaller, less liquid stocks is more common at larger institutions. Second, we find that banks, pensions, and insurance-company portfolios are less concentrated in smaller stocks, consistent with a higher burden of due diligence. Finally, institutions with individual clients are relatively averse to smaller stocks compared to institutions with pooled investment vehicles. The latter can more efficiently monitor; the former face redundancies in monitoring costs.

Our analysis of the alternatives to size-related segmentation provides insight into the economic basis for institutional segmentation in equity markets, and why that segmentation is perversely more severe at smaller institutions. Small institutions tend to not venture outside of the institutional segment of equity markets, despite having an apparent implementation advantage, because they are most constrained by agency considerations.

Our last analysis of the determinants of segmentation derives from a second dimension where the ceteris paribus underlying scale-driven segmentation is doubtful. One of the most obvious motives for an institution to consider a stock for investment is expected profit; i.e., revenue (in the form of paper-portfolio alpha) minus cost (in the form of portfolio implementation). The ceteris paribus of scale arguments implies that only the cost side matters. We provide novel evidence on the importance of the production side. In particular, Form ADV provides data on the number of registered investment advisers (RIAs) at the institution. We find that segmentation effects are far less stringent at institutions with high RIA, controlling for all other factors.

This provides another explanation for why small institutions might avoid small stocks: they *don't* have a comparative advantage in information production there. That is, if adverse selection from weak information is high outside of the 'institutional segment,' then it might be unprofitable for an institution to venture out there even if their implementation cost are zero. That is, small institutions adhere most stringently to the segment. The sweet-spot for smaller institutions may be more in the middle-capitalization range where information is available to them at fairly low cost, but their implementation advantage still has some merit.

Though we do not analyze them, it is not hard to imagine *economies* of scale in information production. These might stem from, for example, ease of acting on information (e.g,, having many opportunities to put capital to work across a wide array of clients and portfolios); or from market power in access to both secondary and primary sources of information; from having market power in attracting labor; and finally from fixed costs of processing and archiving information.

Our study is organized as follows. Section 2 outlines the data and how institutional ownership relates to stock capacity. Section 3 summarizes the inputs and functional forms to our IO specification, and comparatively analyzes model fit. Sections 4.1 and 5 analyze how institutional characteristics relate to segmentation, including both size and agency / informational considerations. Section 6 concludes the paper.

2. Data and variables

Our data consists of portfolio holdings at the institution level for all institutions as well as at the fund level for mutual funds; manager characteristics at the institution level; and returns and characteristics of stocks held.

2.1. Data sources

Our primary source for institutional portfolio holdings is the Thompson Reuters 13F dataset. In addition to holdings data, the Thompsons database also provides the institution's legal type.[1] We merged these data with the CRSP and Compustat databases to incorporate stock characteristics (trade and accounting information) of portfolios, and to incorporate institutional ownership (IO) into factor returns. The merged dataset is quarterly and spans

[1]The Thompsons type codes are not reliable after 1998. We obtain corrected data from Brian Bushee's website, http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

1983 to 2018.[2] We exclude non-U.S. institutions and only keep domestic equity listed on the NYSE, AMEX, or NASDAQ with a share code of 10 or 11. The final data set includes 2801 unique money managers (on average 876 per year).

We also use portfolio holdings from the CRSP mutual fund database as a robustness check on the 13F data, and CRSP returns data for the performance analysis. We repeat the above merging and cleaning process for the holdings data. Note that CRSP mutual-fund holdings are available only after 2002. We focus on equity funds, requiring that on average over the sample, at least 90% of the fund's assets be invested in common stocks for a fund to be included in the sample, following the procedure in Kacperczyk et al. (2008). After aggregating different classes of the same fund into a single observation, the final data set includes 3,799 unique funds (on average 1,404 per year).

For both 13F and CRSP mutual fund database, we employ two screens to avoid the incubation bias documented by **?**. First, funds and money managers must be at least 3 years old to be included in our sample. Second, we exclude funds and money managers whose average net fund assets are below $5 million in the sample.

We also use data from SEC form ADV, which must be filed by investment advisers managing more than $25 million. Form ADV consists of two parts. Part 1 provides information about the investment adviser's business, ownership, clients, employees, business practices, affiliations, and any disciplinary events of the adviser or its employees. Part 2 is a narrative brochure, which describes the types of advisory services offered, fee schedules, disciplinary information, conflicts of interest, and the educational and business background of manage-

[2]The Thompsons database is available as far back as 1980. However, we exclude years before 1983 because daily trading volume for stocks is not available prior to 1983.

ment. We focus on item 5 of Part 1, which describes the advisor's business, including the number of investment advisor personnel, the client structure, and the amount of regulatory assets under management.[3] Clients are classified into fourteen categories, which we aggregate down to six. We merge these data with the 13F data, matching on manager name using condensed word vectors.[4] The merged 13F/ADV covers more than 75% of the 13F manager numbers appearing between 2000 to 2018 in the Thompson database.

2.2. Calendar summary of observations

Figure 1 summarizes the number and size of stocks and institutions in the sample. Both the stock and institution populations changed dramatically over our sample period. While the number of listed stocks historically trended upward (Chart 1A), it began a downward trend around 1998 as documented in Doidge et al. (2017). Simultaneously, the number of institutions steadily increased, causing the ratio of number of institutions to stocks (Chart 1B) to increase by almost an order of magnitude over the sample period. By the end of our sample there is almost one 13-F institution for every publicly traded stock. The aggregate market capitalization of stocks and the aggregate assets under management of institutions have both trended upward over the entire sample period (Chart 2A). As noted in many prior studies, institutions have come to dominate U.S. equity markets.

[3]Prior to October, 2017 the assets of financial advisors was only an approximation. Afterwards it became exact.

[4]We use various screening criteria to drop unreliable matches. For example, we compare the reported assets under management in both samples and dropped matched observations with difference above specific thresholds. Additionally, S34 provides aggregated observations and some money Managers in S34 data set may fill several Form-ADV. In this setting, we manually match several Form-ADV observations with S34 and aggregate them.

2.3. *Capacity and implementation costs*

We say that a stock has low capacity for institutional ownership if acquiring a meaningful position makes an institution a salient trader (i.e., causing discernible price pressure) or owner (e.g., requiring regulatory disclosure). We score stocks according to the median institution by EUM. Our premise is that segmentation occurs when low capacity makes it futile for an institution to incur up-front costs of due diligence – they can't acquire a meaningful position even if the stock passes due diligence. As a result, the stock is excluded from the institutional segment of equity markets.

We define a stock's capacity for institutional holdings, $Capacity^{Hld}$, as the ratio of the stock's market capitalization to the concurrent median EUM of institutions. For example, a $Capacity^{Hld}$ of 0.3 implies a relatively visible 5% ownership stake for the median institution, assuming a 1.5% portfolio weight. By contrast, a $Capacity^{Hld}$ of 7.5 implies a much less visible 0.5% ownership stake. Figure 1, chart 3B displays a striking upward trend in $Capacity^{Hld}$ beginning around 2002, leading to an order of magnitude increase by 2018.

We define two measures of trading capacity. $Capacity^{Trd}$ is the ratio of the stock's median ten-day volume over the year divided by the median institution's EUM in that year. $Capacity^{Trd}_{min}$ is similarly defined using the minimum volume over ten consecutive trading days in the preceding year, meant to proxy for worst-case (left tail) capacity. For example, a $Capacity^{Trd}$ of 0.1 implies a highly visible expected order imbalance of 0.015 / 0.1 = 15% spanning ten days, assuming a 1.5% portfolio weight. The expected price impact from such trading salience would likely eliminate any 'paper' information advantage the institution held, making it futile to acquire information in the first place. By contrast, a $Capacity^{Trd}$ of 10 implies a relatively transparent 1.5% participation rate, making it much easier to implement an information advantage.

Figure 1 is also noteworthy in consideration of Gompers et al. (2003), whose sample end (1996) is denoted with a vertical line in the charts. The US equity market has taken a rather sharp turn since their sample on two counts. First, from Chart 1B, in their sample there were many stocks and few institutions. Now, the counts are roughly equal; meaning more institutions per stock and a mechanical increase in ownership as measured by number of institutions. Second, from Chart 3B, the typical stock's capacity for institutional ownership improved dramatically almost immediately following the Gompers and Metric sample period. Thus, as institutions have come to dominate equity markets, so too have equity markets changed in a way that conforms to institutional demands for capacity. Thus, Figure 1 provides is an early indication that institutional segmentation changed around the turn of the millennium.

Capacity variables relate a stock's size and trading volume to the concurrent size of a typical institution. We also consider three basic 'stock-only' measures of capacity that do not scale to the concurrent median institution size.[5] These are comparable to the numerator inputs to the *Capacity* measures: (1) the stock's market capitalization denoted *MktCap*, (2) $Turn^{MSCI}$ which is essentially a monthly measure of volume divided by market capitalization, and (3) FOT which is the 'frequency of trading' equal to the number of days in the year that the stock traded, divided by the number of days the market was open.[6] We do not tabulate these alternative measures as they yield similar results, but we occasionally refer to them in

[5]Further, we considered normalized versions of both capacity and stock-only explanatory variables, where the value for a given stock is divided by the concurrent mean across all stocks. In the end they yield no improvement in explanatory power for IO.

[6]These follow procedures used by Morgan Stanley Capital International (MSCI) in constructing investable indices (MSCI (2010))

the discussion.

2.4. IO variables

Our primary metric for institutional ownership is the number of institutional owners normalized by the concurrent total number of institutions, i.e. fractional number of institutional owners or *FNIO*. We also define *FSIO* as the fractional shares of institutional ownership, i.e. aggregate shares held by institutions divided by shares outstanding.[7] Figure 2 presents histograms of both *log FNIO* (first row) and *log FSIO* (second row) over the three 12-year periods that we use to partition our sample. (In fact, we add 0.001 to both to avoid an undefined log.) From Panel A (*FNIO*), there is a clear trend in the distribution of institutional ownership. In the early period, There are many zeros, and where positive *FNIO* is low for many/most stocks. Later the norm is more substantial *FNIO*, with *log FNIO* approaches a normal distribution. Panel B likewise clarifies the somewhat discrete nature of IO across stocks. In the early years, many stocks have $FSIO = 0$, whereas the distribution of *FSIO* for institutional held stocks is much higher. In the later years, essentially all stocks fall in this latter distribution, which has shifted to a much higher mean level of *FSIO*.

2.5. Descriptive statistics on capacity and institutional ownership

Statistics in Table 1 are presented in three rows corresponding to 12-year subperiods ending in 1994, 2006, and 2018. Panel A summarizes stocks, and Panel C summarizes stocks

[7] Investment activity can be measured in terms of the number of actions by agents (i.e., number of trades or owners in a stock), or by the aggregate magnitude of those actions (i.e., percentage of shares outstanding traded or held). This is a considerations in both the microstructure and institutional investment literature (for example, Jones et al. (1994) or Sias et al. (2006). In most cases the count-based metric has more empirical relevance. Our evidence is consistent with that finding – the numbers-based metric is better explained by stock characteristics and it does a better job of identifying IO factors and their impact on performance evaluation.

partitioned by the size of institutions holding them. Panel B summarizes institutions more broadly. Many of the statistics echo the trends seen in Figure 1. For example, from Panel A, note that the fraction of stocks that are institutionally held increases substantially, from 80% (4750/5936) to 94% (3722/3939). Likewise (as is well known), the fraction of shares outstanding held by institutions (*FSIO*) has also increased substantially, to a median of about 60% in the later period. The number of institutions owning the median stock (*NIO*) has also increased substantially, from 10 to 85. The fraction of institutions holding the median stock (i.e, median *FNIO*) increased more modestly, from 1.1% to 2.7%.

The capacity summary statistics in Table 1, Panel A emphasize the striking improvement for stocks in the most recent sample period. The median stock now offers substantial room for anonymous ownership in even the largest EUM quintile. For example, with a $Capacity^{Hld}$ of 2.58, a 1.5% portfolio weight means owning 1.5%/2.58 = 0.6% of the typical firm's shares outstanding. This compares favorably to the first period where a notional 1.5% portfolio weight means owning 5.8% of shares outstanding. Likewise, the median stock's trading volume has a much higher ability to absorb the demands of even large institutions. Acquiring a notional 1.5% portfolio weight over ten days means a 9% order imbalance in the last period, compared to 333% in the first period. These improvements are echoed in the summary statistics for basic measures of capacity. Evidently, the stock market has become far more accommodating to institutions with the millennial transition identified in Doidge et al. (2017).

From Table 1 Panel B, the number of stocks per institution has almost halved over time, from a median of 115 to 63. While this conceivably stems from a similar reduction in median EUM (e.g., from 332 to 224), that explanation is at best incomplete. There is no reduction in the EUM of largest-quintile institutions, yet they too hold only half as many stocks in the most recent period. An alternative explanation is that the stocks themselves are now much more accommodating of a large portfolio weight. We also note a very low median EUM for institutions in the bottom EUM quintile (e.g., \$32 million in the last 12-year period). While institutions must manage \$100 million to make it into the 13F dataset, they stay in that dataset for up to seven quarters even if they decline in size.[8] Likewise, the median number of stocks held is quite low in the bottom EUM quintile (e.g., 23 in the last 12-year period).

Table 1 Panel C presents characteristics of stocks held by institutions in the indicated quintile of EUM (column heading). For every measure of caoacity(be it the scaled *Capacity* measures or the basic 'stock-only' measures), we see the curious result that the median stock for smaller institutions has far greater capacity than the median stock for large institutions. For example, the median stock held by quintile-1 institutions has ($4.05/3 = 13.5$, $17.0/1.75 = 9.7$, and $49.5/11.1 = 4.5$) times the trading capacity in the early, middle, and late periods, respectively. The same holds for other capacity metrics, and for the stocks' *FNIO*, *FSIO*.

This pattern does not align with an implementation argument that smaller instituions can more easily acquire meaningful portfolio weight in stocks at the fringe (or outside) of the institutional segment of equity markets. However, it does align with a contracting perspective, in the sense that stocks with high capacity and lots of institutional ownership might be considered 'certifiably prudent.' The clientele of a small institution, with a relatively fragile reputation, is likely more sensitive to agency concerns than the clientele of a large institution with a reliable reputation. Thus, the small institutions has a strong incentive

[8] To confirm this explanation we searched over the preceding seven quarters for the maximum AUM for each manager. For the median institution in the smallest EUM quintile, this value is almost \$150M.

to limit their attention to only certifiably prudent stocks. The shadow cost of holding 'speculative' stocks (in terms of impediment to new clients and exodus of existing clients) is just too great.

3. Inputs and functional form of IO

Figure 2 provides histograms of *FNIO* and *FSIO* across the three subperiods in our overall sample. Consistent with segmentation, the figures suggest a two-level consideration of aggregate IO: a binary (logit) regression analysis of a stock being institutionally held or not (i.e., indicator for $NIO > 1$); and a continuous regression to analyze the magnitude of aggregate ownership conditional on $NIO > 1$. Thus, in this section we develop both a continuous model of expected IO given $NIO > 1$, and a binary model of a stock being institutionally held or not. Combining the two we end up with a functional form for institutional ownership that suggests segmentation driven almost entirely by the capacity of the stock's market.

3.1. Specification

We conduct our analyses using four categories of stock characteristics that potentially relate to institutional preferences, as outlined in Gompers et al. (2003) and Lewellen (2011). The first category is captured by our three *Capacity* measures, as described in Section 2.3. Additionally, we consider index dummies (S&P 500, Russell 1000, and Russell 2000); market characteristics (price, beta, momentum, reversals, and volatility); and firm fundamentals (firm age, B/M ratio, asset growth, and ROA).

We consider four functional forms for the continuous model – levels, logs, and two logistic transformations.[9] These are tabulated for *FNIO* and *FSIO* in Table 2, Panels A and B, respectively (more specifically, we tabulate the regression R-squared). Each column presents a separate regression with the indicated set of regressors. The 'all' column includes all categories of explanatory variables.

The logistic transformation is essentially a smoothed, S-shaped step function with a parameterized rate of transition from a lower bound (in our case zero) to an upper bound:

$$IO = \frac{L}{1 + e^{-(b_0 + b_1 x_1 + b_2 x_2 + \ldots)}}, \tag{1}$$

where L is the upper asymptote on IO (zero is the implicit lower bound) and the x regressors (i.e., stock characterstics) are either in levels (denoted 'Logistic') or in logs (denoted 'Logistic^{log}'). A stock that falls near the lower bound is considered 'out' of the institutional segment of equity markets. A stock in-transition, or at the upper bound, is 'in.' We estimate this with nonlinear least squares.

The dependent variable in Table 2, Panel A is the level of *FNIO* or *FSIO* except in the case of log regressors, where we also use a log dependent variable. The tabulated R-squared for this log-log specification is from a second regression where the level of the dependent variable (i.e., *FNIO* or *FSIO*) is regressed on the exponential of the fitted value from the log-log regression. This makes the R-squareds comparable.

Table 2, Panel C presents the binary analysis, which is a pooled logit regression with time fixed effects. The dependent variable is an indicator for $NIO > 1$. Observations are

[9] In results not tabulated, we also consider specifications where We scaled by the concurrent cross-sectional mean *NIO* to de-trend (denoted NIO_{EW} and NIO_{VW} depending on the mean weighting scheme). Similarly, we considered FIO_{EW} and FIO_{VW}. None provided relevant improvement.

weighted using the number of observations per period. We report Max-rescaled r-square which uses likelihood-based pseudo-R-square and follows Nagelkerke's adjustment to reach a maximum value of 1. We consider two specifications for regressors – levels and logs – and the same set of regressor categories.

3.2. Results

Comparing Table 2, panel A and B, we see that the *FNIO* regressions consistently fit better than the *FSIO* regressions. However, because the patterns across the two metrics is similar, we couch much of our discussion in terms of *FNIO*. [We also note that we repeated the table using only the basic 'stock-only' measures of capacity (market capitalization, turnover, and frequency of trading unscaled by median EUM). This yields comparable explanatory power.[10]] The more important observations on Table 2 relate to functional form and the other input variables.

3.2.1. Functional form

First consider functional form. For now, we restrict our attention to the case of capacity predictors only, i.e., the first column of Table 2. The levels-on-levels specification performs relatively poorly (32.6% for *FNIO*; 20.5% for *FSIO*). The fit improves dramatically as we introduce nonlinearity into the relation, with the 'Logistic^{log}' specification providing the highest explanatory power, 90.7% and 57.8% for *FNIO* and *FSIO*, respectively.

[10]We understand this as follows. Scaling by median EUM can only improve the fit to time-series variation. In results not tabulated, we find that time-series variance in the mean *NIO* across stocks accounts for only 11.1% of the variance in *NIO*. Moreover, this time-series variance is explained equally well using the trend in market capitalization and the trend in capacity (r-squared of about 96% in both cases). In other words, scaling by concurrent institution size cannot improve upon the explanatory power of stock-only variables. To examine this we ran a panel regression of *NIO* on a regressor that assigns the concurrent cross sectional mean *NIO* to each observation, and found an Rquare of 11.1%. We then regressed the mean *NIO*s on a similarly constructed mean market cap and mean capacity. The Rsquares were 96.7% and 95.9%, respectively.

Figure 4, Panel A provides a graphical depiction of these estimated Logistic^{log} relations in each of three time periods. Below each is a frequency distribution of stocks by log capitalization in the corresponding periods. Combining the substantial increase in explanatory power seen in Table 2 with the functional form depicted here, we infer that segmentation based on a stock's capacity is a key component to institutional ownership.

3.2.2. Other stock characteristics

An alternative inference one might draw from Table 2 is that preferences for the other categories of characteristics explain IO. This hypothesis seems to be supported in the levels-on-levels specification. In particular, from the first row of Panel A (B), the R-squared increases by a factor of 2.3x (2.4x) for *FNIO* (*FSIO*). However, the resulting explanatory power still falls far short of that obtained with the Logistic^{log} specification using just *Capacity* (74.0% vs 90.7% and 48.7% vs 57.8% for *FNIO* and *FSIO*). Moreover, almost all of the increase comes from index indicators, which are obviously a segmentation proxy.

If we make the same observation with the logs-on-logs specification, the case appears to be stronger. Yet, the segmentation specification (Logistic^{log}) still performs substantially better using only *Capacity* inputs. Moreover, in looking at the first column (*Capacity* only) it is clear that the improvement comes from segmentation effects. Using logs-on-logs the dramatic explanatory power from index indicators (clearly reflecting segmentation) is now subsumed (e.g., 85.0% vs 86.0% in the case of *FNIO*).

We conclude that the evidence here establishes institutional segmentation in equity markets. Stock characteristics beyond capacity improve explanatory power slightly, using the Logistic^{log} specification, but the increase is slight (R-squared improvement from 90.7% to

92.4%. We thus take our final specification to be the parsimonious (Logistic^{log}) functional form using only *Capacity* inputs.

These patterns are broadly consistent for *FSIO* in Table 2, Panel B though, as noted above, the explanatory power is lower. Again the Logistic^{log} specification performs best, with the basic *Capacity* inputs providing an Rsquare of 57.8%. This specification again subsumes most of the collective explanatory power of the other input categories, but the Rsquare does rise to 61.8% indicating some relevance to other determinants. Finally, the patterns are also broadly consistent for the binary specifcation in Table 2, Panel C.

3.2.3. Mutual funds

The preceding analysis – and most of our study – pertains to 13(f) institutions which reflect the advisers' aggregate portfolio. We believe that this is the appropriate level of analysis to explore aggregate segmentation in the equity markets. However, it is of interest to see if similar results obtain for mutual funds, which are dis-aggregated portfolios. From Figure 4, Panel B we see that the same segmentation pattern obtains.

3.2.4. Depiction of fit

Figure 3 provides a visual depiction of the fit of actual to predicted *FNIO* and *FSIO* using the various specifications in Table 2. From Panel A, the logs-on-logs specification tends to forecast fairly well. However, at higher levels the forecast understates *FNIO* (the plots are above the identity line). Moreover, the plots are more diffuse at higher values (the plots would be more dense and dark with a precise forecast).

From Figure 3 Panel B, The Logistic specification fixes this bias at the high end, but it does so via an arbitrary truncation. This reflects the curvature of the logistic function, which is designed to asymptote on some saturation level of *FNIO*. Levels forces this truncation too soon. Moreover, the forecast remains diffuse at higher values. From Panel C, adding a log transformation of the regressors before incorporation into the logistic function, as in the Logistic^{log} specification, fixes these problems by moderating the influence of extremely large values. Similar comments apply for *FSIO*.

The evidence in this section suggests that institutional ownership of a firm's stock is determined almost entirely by the capacity of the stocks' market, and that this dependence takes the form of a segmenting of investment to stocks with sufficient capacity. In the next two sections we tie this to characteristics of the institution to investigate the extent to which implementation costs and contracting considerations explain segmentation.

4. Institution size and segmented investment

Implicit in the notion of *Capacity* is an expectation of an increasing need for segmentation at larger institutions. This presumes an implementation-cost motive for stock exclusion, as discussed in Section 2.3.

The summary statistics in Table 1, Panel C provide early evidence that something is amiss with this premise. There is a curious inverse relation between institution size and segmentation. In particular, quintile-1 (small) institutions by EUM hold stocks with high median capacity (e.g., $Capacity^{Hld}$ 3.44 in the middle period) and institutional ownership (e.g, *FSIO* 56%). Quintile-5 institutions hold stocks with much lower median capacity ($Capacity^{Hld}$ 0.66 in the middle period) and IO (*FSIO* 34%). The same is true for $Capacity^{TRd}$ and *FNIO*; and all time periods.

In this section we take a close look at how segmentation in IO relates to institution size. Our findings confirm the counter-intuitive result that segmentation effects seems to be strongest at smaller institutions.

4.1. Partitioned sample summaries

As a first step to investigating how IO patterns relate to institution size, Table 3 summarizes IO by the stock characteristics used in the Table 2 regression analysis, separately across quintiles of institutions sorted on EUM. Each column of Table 2 represents a different quintile of institutions' EUM, and each row represents a different quintile of the indicated stock characteristic (independent sorts). The cells present the median *FNIO* (Panel A) and *FSIO* (Panel B) within the indicated range.

As expected, IO increases monotonically with respect to each predictor within EUM quintiles, indicating a universal preference for stocks with greater *Capacity.* Market cap and average 10-day volume provide essentially identical univariate explanatory power (spread in IO across quintile sorts) for *FNIO*.

Also from Table 2, IO increases monotonically across quintiles of EUM for a given quintile of stock characteristic. *Ceteris paribus*, this might be expected since larger institutions tend to hold more stocks (implying a greater expectation of a large institutional owner for any stock). However, diseconomies of scale in portfolio implementation strongly rejects the *ceteris paribus* premise. Small institutions should have a comparative advantage in informed trading in small stocks and large institutions should face heightened implementation constraints. That is, despite an increased number of holdings, large institutions should nevertheless restrict attention to large stocks. Table 2 does not support this diseconomies of scale argument.

This result is repeated in several of our analyses below. While there are plausibly other dimensions of scale diseconomies, the capacity issue would seem to be a dominant consideration. For example, it figures prominently in Berk and Green (2004), who state (page 1273) "These assumptions capture the notion that with a sufficiently large fund, a manager will spread his information gathering activities too thin or that large trades will be associated with a larger price impact and higher execution costs." Yet, it appears that smaller institutions are just as sensitive to capacity considerations – if not more – than large institutions.

4.2. Partitioned sample graphs

Figure 5 details institutional ownership across ventiles (20 ranked bins) of stocks' size in each of the three 12-year periods in our sample. Panel A (B) presents *FNIO* (*FSIO*) for the mean and median stock against market cap ventiles. Each chart presents quintiles one, three, and five(largest) of institutions by EUM. Here both *FNIO* and *FSIO* are defined within quintiles; that is, the denominator in each case corresponds to the set of institutions within the quintile, not the set of all institutions. Note that because *FNIO* can be zero, we add 0.001 to the argument in the log-scaled charts to avoid unbounded negative values.

Our discussion focuses on the middle twelve year period, but patterns are similar in the other periods. From both Panels A and B, first note that the median stock in the smallest ventile of capacity (meaning, either market cap in Panel A or trading volume in Panel B) has at least one institutional owner from the largest EUM quintile, but no ownership by institutions in the smaller quintiles. This pattern continues at higher ventiles of capacity. It is not until around ventile seven that the median stock has at least one smallest-quintile institutional owner. Panels A and B also reveal a noteworthy pattern to the slope of $\log(FNIO)$

with respect to a stock's capacity ventile. For the largest institutions, $\log(FNIO)$ increases essentially linearly across capacity ventiles. For smaller institutions, the increase in holdings is minimal until around ventile fifteen, at which point IO becomes very sensitive to further increases in capacity.

Implementation considerations should be most pressing for the largest Q5 institutions. Yet, we see these institutions acting seemingly without regard for capacity in defining their investable universe. Yes, they prefer higher capacity, but their investable universe appears to include all stocks. By contrast, the institutions that one expects to have the least pressing need to consider implementation costs (smaller Q3 or Q1 institutions) seem to constrain their universe based on capacity. Their investable universe is clearly segmented by the capacity characteristics.

Further support for this pattern of IO is provided in Figure 4 Panel B, which details the Logistic^{log} specification of *FNIO* by EUM quintiles. The noteworthy observation is again that the larger the EUM quintile, the less sensitive the institution is to the stock's market capitalization. This runs contrary to the intuition of increased implementation constraints for larger institutions.

Our evidence runs counter to the hypothesis that constraint are determined by implementation costs alone. Specifically, The small institutions that are best positioned to exploit mispricing in small capitalization stocks from a trading cost standpoint, seem least inclined to pursue such opportunities. Implementation costs do not explain this pattern. In what follows we explore whether agency concerns might help explain. First, however, we consider the robustness of our findings to portfolio considerations.

4.3. Fund-level analysis

Form 13F holdings data is aggregated at the institution level, so one entity may represent many separate accounts and funds. For example, Fidelity (MGRNO=27800) reports as a single entity and aggregates the holdings of all funds and trusts that it manages. Arguably, implementation costs occur at a portfolio level, and it is the *portfolio* size, rather than institution size, that affects investment behavior. Thus it may be that large managers specialize in offering small portfolios, each if which invests in small, illiquid stocks. That is, institution size is not a good proxy for the relevant metric of portfolio size.

There are a couple of reasons to question this. First, trading is typically aggregated (Edelen and Kadlec, 2012) at the manager level so it is not clear that many small portfolios would avoid implementation issues. Second, a large institution may not find it worth their while managing funds focused on small, illiquid stocks, unless those funds become quite large. But that of course unravels the argument. However, it is possible that large institutions have a reputational advantage in managing investments that lie in uncharted territories (small stocks). A smaller institution may find it difficult to convince investors that agency conflicts are not a concern.

To address this issue, we repeat the analysis of market cap ventiles using mutual fund holdings in the bottom row of charts in Figure 5. the results confirm the findings with 13F institutions: Larger portfolio managers are more likely to hold smaller stocks.

5. Form ADV institutional characteristics

Section 4.1 relates segmentation to institution size. But institutions are heterogeneous on other dimensions that potentially relate to segmentation. For example, the cost of and need for due diligence might relate to the institution type or the clientele, or to regulations, governance, and other contracting considerations. Our empirical analysis here explores how segmentation sensitivity relate to institution type using both standard categories for managers and Form ADV data on institutions' clientele and personnel.

We first summarize these new data (Section 5.1). We then conduct our analyses in Section 5.2 and Section 5.3.

5.1. Summary characteristics of institutions – Form ADV data

Table 4 provides summary statistics on the data from Form ADV filings merged with the Form 13F and covering the years 2000-2018. From Panel A, the sample contains on average 2215 unique managers each calendar year (5159 in total). The median institution in the merged sample has $250 million in EUM invested in 73 different stocks. This is comparable to the 13F sample over the same period as summarized in Table 1. Form ADV provides total asset under management (AUM), which has a median value of $710 million. Thus, approximately 44% of institutional AUM is invested in equity.

Table 4, Panel A also provides summary statistics by category of institution (taken from the 13F data). Investment firms are by far the most common category, representing 94.8% of institutions by count; 85.5% by assets; and 77.4% by equity investment. Banks are a very distant second-most frequently observed category at 2.9% by count. However, because a few banks are very large,[11] banks account for a disproportionate 17.3% of overall EUM from institutions. Insurance companies are also very large, and they along with pensions tend to hold the smallest fraction of AUM as equity (18% and 27%, respectively). Banks

[11] Note that the ratio of mean to median at banks indicates a very high industry concentration ratio.

and investment advisers hold closer to half of their AUM as equity. Recall, 13F holdings are equity only. For each institution we divide EUM by the number of equities held to get an average position size. Insurance companies and pensions tend to hold relatively large positions (around \$5.6 million versus around \$3.5 million for banks and investment advisers.

Table 4 Panel B and C summarizes the Form ADV data on an institutions' clientele and personnel. These data turn out to be key dimensions for characterizing institutions.[12] About 51% of clients by count are individuals, representing about 41% of AUM. The column labelled 'per' is the ratio, or \$M account size per client. Not surprisingly, individuals are comparatively small. The remainder is dominated by pooled investment vehicles, which tend to have a relatively large average account size. Insurance company clients have the largest average account size, but they are not large in number (1.1% of the typical clientele). Bank clients are also few in number, with smaller account sizes. This suggests (perhaps not surprisingly) that when banks farm out their investment management it is typically not a large amount. The typical institution employs 84 registered investment adviser (RIAs) but this variable is intensely skewed. Indeed, all personnel variables are highly skewed. We work with RIAs scaled by a variety of measures (EUM, stocks held, and clients).

5.2. Overview of analysis

The aim of Section 5.2 is to examine how characteristics of the institution relate to characteristics of stocks held. Regarding stocks held, the characteristic of interest is the extent to which the stock appears to be institutionally segmented. We proxy this with

[12] Form ADV lists 14 categories of client that we compress to 6, for example combining: individual and high-net-worth (accredited investors); investment companies and pooled investment vehicles; and sovereign wealth and government entities. See https://www.sec.gov/about/forms/formadv-part1a.pdf.

the stock's *FNIO* and *FSIO*. Regarding institutions, the characteristics examined relate to EUM, trading, and flow, and to their clientele and information production. We also look at standardized classifications (bank, insurance, pension, and investment manager). In this section we report the number of positions and dollars invested in each *FNIO*-quintile of stock. We look at the effect of institution characteristics in a regression setting in the next section (5.3).

5.2.1. Categories of institutions

Figure 6 and 7 parallels Figure 5 for ADV characteristics. In particular, Figure 6 (7) graphs *FNIO* (*FSIO*) across quintiles (20 ranked bins) of stocks' size from 2000 to 2018. Both *FNIO* and *FSIO* are defined within quintiles; that is, the denominator in each case corresponds to the set of institutions within the quintile, not the set of all institutions. From Panel A, Figure 6, we observe that the ownership of small stocks are mostly from investment advisors and banks. Thus, investment advisors and banks appear to be less segmented in their investing. Pension and insurance firms appear to be more constrained in their holdings. A similar pattern is seen in Figure 7 with $\log(FSIO)$.

Banks' segmentation pattern is curious since banks are supposed to be the most constrained, prudent institutions. The bank plot (Panel C) makes it clear that it is indeed a few very large banks that drives our finding. In fact, most banks appear to be highly segmented in their investment, holding only stocks in the the top quarter of market capitalization. This contrast across EUM quintiles is also seen at pensions and insurance companies, where again one expects prudence to be relatively important. The contrast across EUM quintiles is not so evident at investment advisers, however. For this type of institution, both large and small firms act relatively unconstrained.

Further support for how standardized classifications related to the holding is provided in Table 5, Panel A. We sort stock into 5 quintile based on the FNIO in each calendar year. Then, by institution, we calculate the fractional number of holding (by count) and fractional dollar invested (by dollar) in each quintile of stocks. Next, we report the average mean fraction of holdings for each stock quintile (e.g., Q1) within each category (i.e., banks). From panel A, first note that investment advisors show the highest and pensions show the lowest concentration of ownership in low *FNIO* stocks.

5.2.2. Clientele

Institutions may have different exposure to reputational capital with regard to their client structures. We thus examine how the clientele of investors interacts with apparent constraints. Table 6 tabulates the holding of institutions based on their clients. In it, rows tabulate sorts on the institution's clientele type (e.g., individuals) and columns tabulate sorts on stocks' NIO. The table then reports on institutions' holdings of stocks within each NIO quintile. In those cases where a particular clientele type occurs infrequently across institutions (e.g., bank clients), the set of non-zero institutions is split into two equally populated groups (low and high). Otherwise, the sorts are grouped by quartile.

Table 6 describes the holding of institutions based on the institutions' clientele. We sort all institutions by the percentage of client dollars from the indicated category (e.g., individuals, or pensions) and divide them into quartiles. We then analyze the investment pattern in each quartile. We also divide stocks into 5 quintiles sorted on NIO (Q5 high) and look at the percentage of an institution's holdings in each NIO bin.

Table 6 indicates that a higher concentration of clients from individual and pension categories (but particularly individuals) is associated with a stronger preference for high NIO stocks. In particular, the fraction of investments allocated to each of the bottom four NIO quintiles is decreasing with an individual clientele; and the fraction of investments allocated to the highest NIO quintile is strongly increasing. This suggests that when the client is a separate account, the investment manager tends to hold 'bona-fide' (high NIO) investments, presumably to alleviate clients' heightened agency concerns.

Conversely, investment managers with a higher concentration of clients from pooled investment vehicles show just the opposite tendency. The fraction of investments allocated to each of the bottom four NIO quintiles is increasing and the fraction allocated to the highest NIO quintile is strongly decreasing. Evidently, the pooling feature of these client types has a tremendous impact on the pattern of IO. Evidently, investors in pooled vehicles are more willing to tolerate adventurous investment, whereas separate accounts (individuals, pensions, etc.) are less trusting of investment managers' due diligence. This could be because a pooled vehicle puts more onus on the manager to do the right thing. Or it could be because shared oversight reduces the cost and increases the effectiveness of monitoring.

Even though investment firms and other professional money managers may be less sensitive to the reputation than individuals, they operate in a different regulatory environment. Institutional managers with discretion over the assets of others are legally considered fiduciaries, but the applicable standard of prudence depends on the nature of clients. For example, bank managers are exclusively restricted by common-law prudent-man rule, since they invest on behalf of private trust and pension plan clients, and are therefore subject to the most stringent prudence standards [Del Guercio (1996)]. Accordingly, unlike the investment firms;

banks, pensions, and insurance invest a higher fraction of their assets into liquid and large assets.

Besides direct and implicit contracting effects, investment managers also operate in a regulatory environment that further restricts their behavior. In particular, regulation protects investment principals (clients) by allowing them to seek damages from a fiduciary (managers) who fails to invest in their best interest. As a result, fiduciaries have an incentive to protect themselves by investing in bona fide, high-quality assets that are easy to defend in court. These regulatory considerations are arguably most relevant at banks, pensions, and insurance institutions. However, they are probably more enforceable for individual clients as well. All of which is consistent with our findings. The fiduciary duties of investment managers or advisors of investment companies are less clear and restrictive than for those governed by common law or ERISA. The Investment Company Act of 1940 explicitly requires that mutual funds must meet various investment diversification standards (e.g., prohibits mutual funds from investing more than 15% of their net assets in illiquid securities). But these likely do not carry the weight of litigation that the fiduciary duty to an individual or ERISA account would.

5.2.3. Information acquisition capacity

An alternative explanation for lessened constraints at larger institutions is that they have more resources and privileged access to sell-side research and corporations, big and small. This facilitates a private-information information advantage over smaller institutions. They recover the cost by way of a *relatively* large asset base (i.e., a small-cap fund with more assets than a comparable fund at a small institution) and by way of bundling externalities (clients that are primarily interested in a large investment in large-cap products nevertheless want a small-cap product from a reputable advisor, and they use flashy performance in the small-cap product as a signal of overall firm skill). On the other hand, small institutions with limited resources restrict their attention to large-cap stocks where information asymmetries are less severe.

Table 7, Panel B examines the effect of the research source of money managers on their holdings. We divide an institutions' count of registered investment advisors (denoted *RIA*) by EUM, frequency of stocks, and frequency of clients to capture the relative capacity of institutions to acquire information. Rows present quartile of institutions sorted by *RIA/EUM*, *RIA/Stocks*, and *RIA/Clients*. We also sort also stocks into 5 quintiles based on the FNIO in each calendar year. Then, by an institution, we calculate the fractional number of holding (by count) and fractional dollar invested (by a dollar) in each quintile of stocks. Next, we report the average mean fraction of holdings for each stock quintile (e.g., Q1) within each quartile of research capacity (i.e., *RIA/EUM*).

From Table 7, it appears that institutions with the largest fraction of *RIA/EUM* show the highest and institutions with the smallest fraction of *RIA/EUM* show the lowest concentration of ownership in low *FNIO* stocks. In addition,institutions with large fraction of *RIA/stocks* move their assets toward the low *FNIO* stocks while institutions with small fraction of *RIA/stocks* move their assets toward the high *FNIO* stocks. More importantly, institutions with a higher number of *RIA* for each client also tend to concentrate their assets on small-cap products.

5.3. Regressions

Table 7 essentially repeats the analysis of Tables 5 and 6 in a multivariate regression setting. This table details the effect of clientele, implementation, information acquisition capacity, and legal type. The dependent variables are the fraction of stocks invested in quintile 1 and 2 (Q1-2), quintile 3 and 4 (Q3-4), and quintile 5 (Q5), where the quintile here refers to the stock's NIO. We measure the fraction of stocks invested both by count of stocks and by the dollar invested in each quintile.

From Table 7a, Panel A, Regression 1, first note that the clientele explains 8.6%, 24.6%, and 24.33% of institution's investment in low, medium and high NIO stocks, respectively. Interestingly, this accounts for about 75% of the total explanatory power that we get adding all other institution characteristics. This further supports the view that segmentation derives more from contracting considerations than implementation costs per se. This inference is important to stories of diseconomies of scale (e.g., Berk and Green, 2004). In fact, because the contracting story goes the other direction (more impediments for smaller institutions), the contracting story also goes in the opposite direction to the conventional wisdom underlying scale arguments. Our results from Table 7 are consistent with Tables 5 and 6. Money managers with a larger clientele of pooled investment vehicles invest a higher fraction of portfolio assets clients is associated with an investments focus on high-NIO stocks.

Investment restrictions motivated by agency considerations are a natural source of constraint in portfolio holdings. Conflicts of interest can arise between an investment manager and their clients, relating to idiosyncratic and portfolio risks of specific investments, perhaps most importantly relating to whether due diligence was performed in assessing the investment's prospects. While the risk of agency conflict with a specific investment is likely correlated with the cost of implementing that investment, the two are not the same. Their difference should manifest most clearly with the size of the institution making the investment. A large institution probably has low agency costs due to reputational capital, but high implementation costs. A small institution has low implementation costs but may find it difficult to dissuade investors from agency concerns.

The most immediate mechanism for reducing client-manager agency conflict is direct contracting. For example, the tracking error constraint as specified in investment contracts restricts the maximal possible deviation of a money manager's portfolio from a given benchmark [Cao et al. (2017)]. Arguably, reputational capital resides at the institution (rather than portfolio) level. A smaller institution has less reputation to protect and therefore may be more willing to act in their own interest when investing in opaque (small, less liquid) stocks. To mitigate this risk, they may be more likely to arrange contracts with their investors that restrict their ability to hold stocks without a bona-fide investor base (i.e., larger-capitalization stocks with substantial IO).

Table 7, regression 2 details the effect of information capacity. We include *RIA* and *RIA* interacted with the number of stocks held by the institution. We observe that for the constant number of securities in the portfolio, institutions with a higher number of RIA move their portfolio toward small and illiquid stocks.

6. Conclusion

Our evidence shows that a stock's capacity for investment is a strong determinant of segmentation in institutional investment. The conventional wisdom holds that implementation costs generate diseconomies of scale. With fixed costs of considering investment in a stock, they also imply segmentation. Our results suggest that this is not the only, or even primary consideration. Contracting (agency costs and monitoring) seems to be an important determinant. Consistent with this, we find that segmentation aligns with: (1) Small institutions with insufficient reputational capital to alleviate agency concerns, who must restrict investment to 'safe' stocks. (2) Institution categories prone to due-diligence concerns. (3) Clienteles with inefficient (redundant) monitoring (e.g, separate accounts) rather than efficient monitoring (e.g., pooled investment vehicles). (4) Low information-production capacity.

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Figure 1

Time series of stocks and institutions

Charts on the left present separate time series for stocks (solid lines) and institutions (dotted lines). Charts on the right present ratios of medians (institutions / stocks in 1B and 2B; stocks / institutions in 3B).

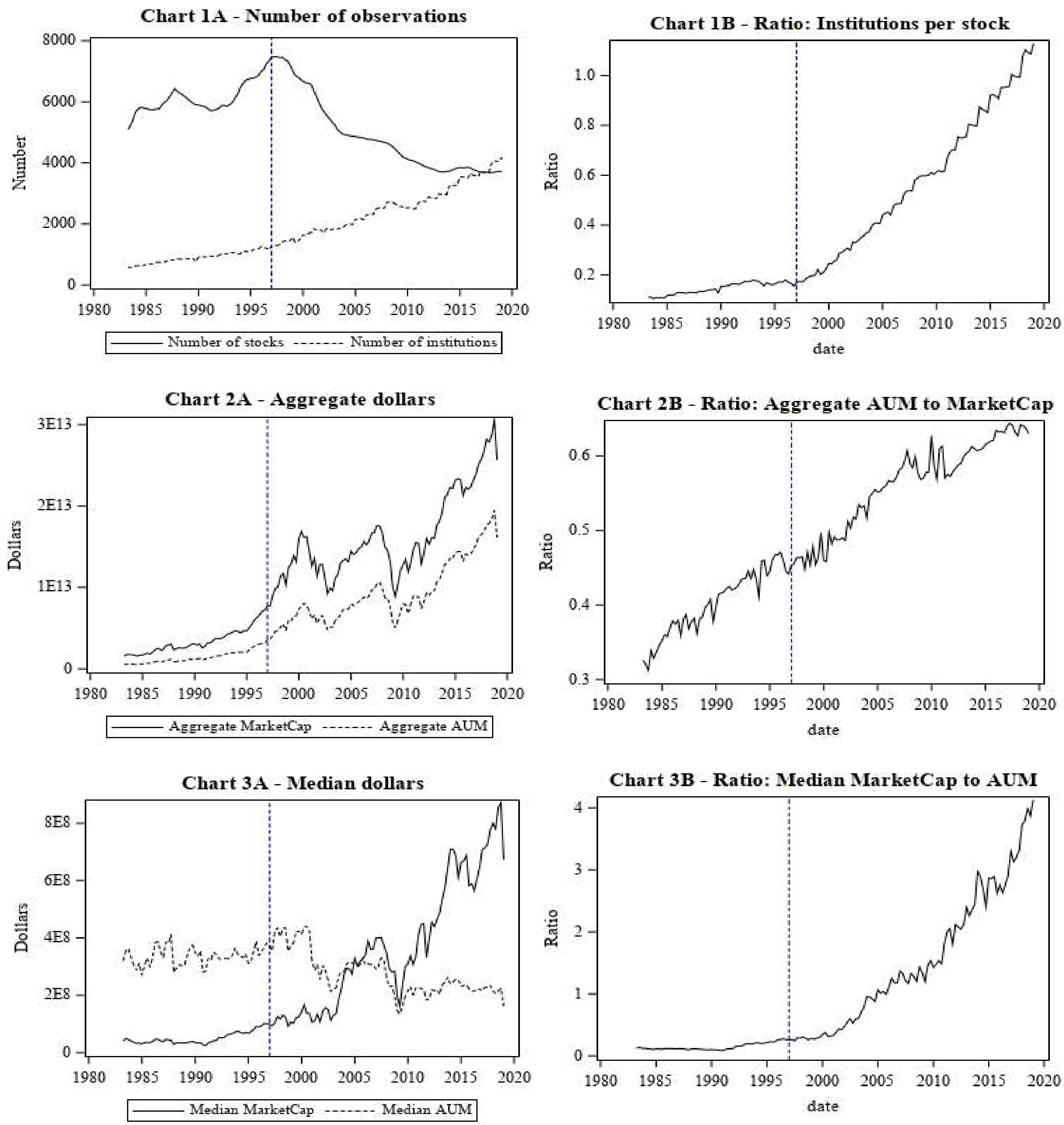


Figure 2

Histograms of institutional ownership

Each column of charts corresponds to a 12 year period of the sample. FNIO refers to the fractional number of institutional owners and FSIO refers to the fractional shares of institutional ownership.

Panel A. Histogram Log (0.001 + FNIO)

Chart A.1, 1983 -1994

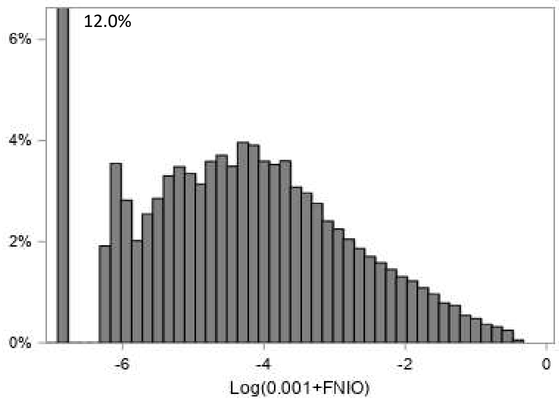


Chart A.2, 1995 - 2006

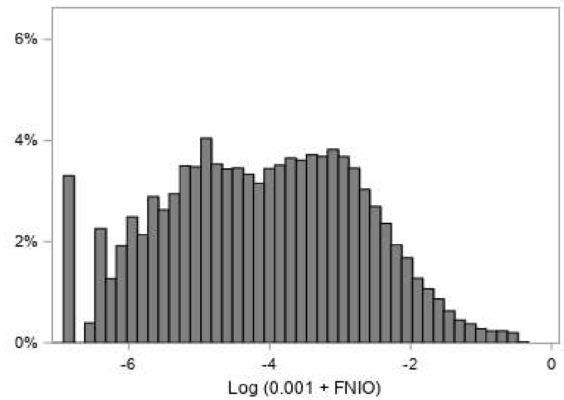
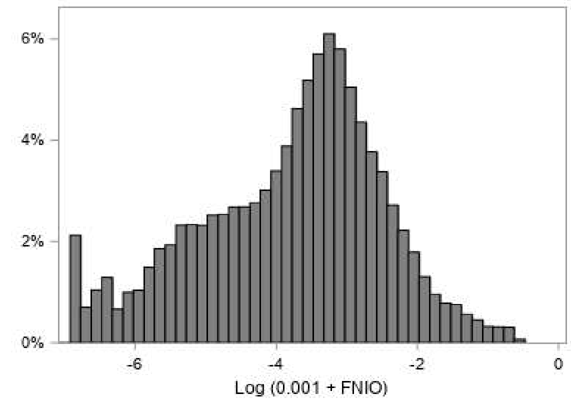


Chart A.3, 2007 -2018



Panel B. Histogram Log (0.001 + FSIO)

Chart B.1. 1983 -1994

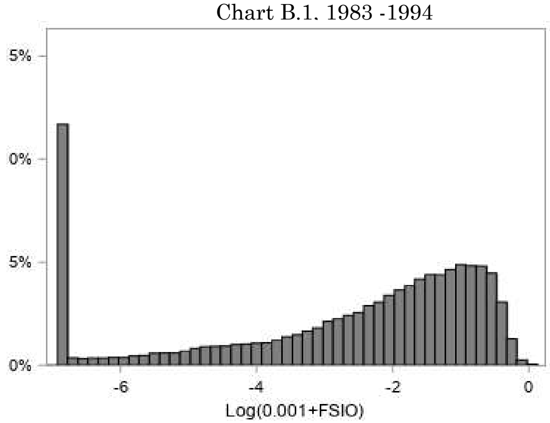


Chart B.2, 1995 - 2006

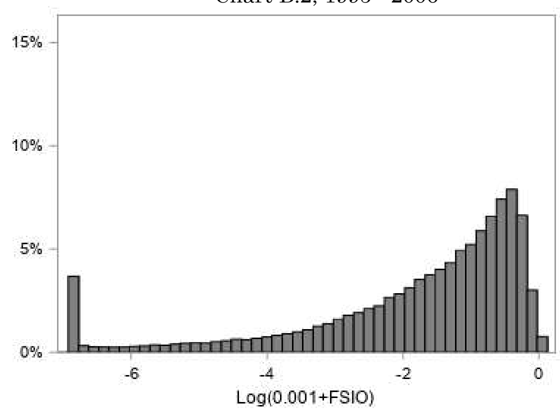


Chart B.3, 2007 -2018

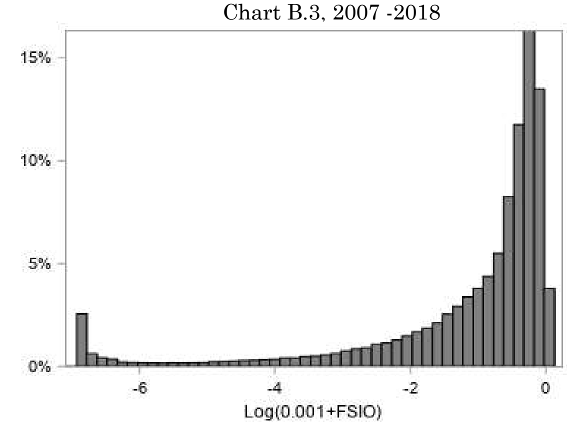
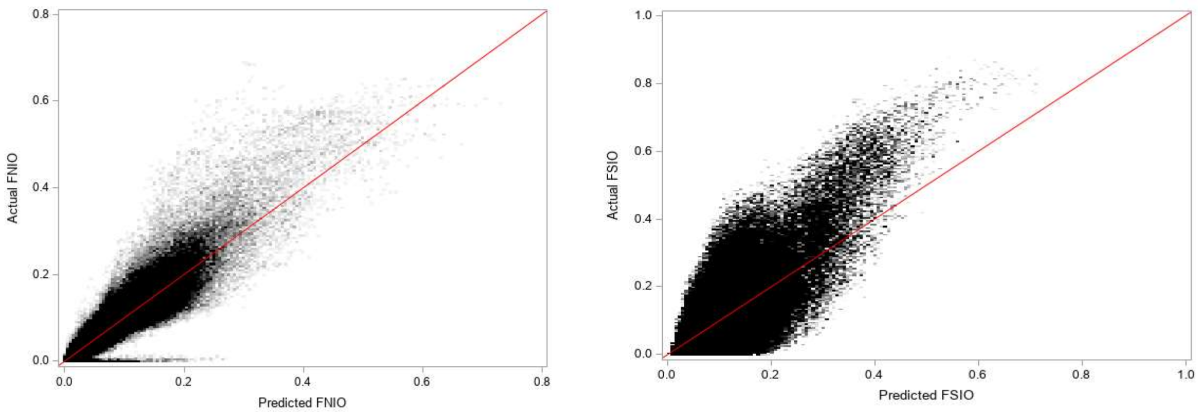


Figure 3

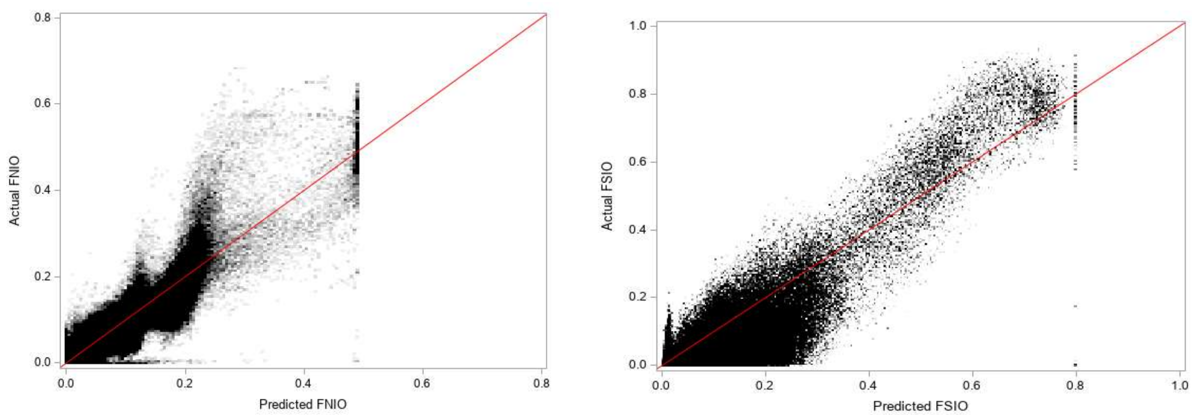
Actual institutional ownership versus predicted, 1983-2018

The charts on the left and right correspond to the predicted fractional number of institutional owners (FNIO) and fractional share of institutional owners (FSIO), respectively. Both columns use stock-only predictors as well as all sets of control variables. Panel A uses a logs on log specification from Table 2. Panel B (C) uses a levels on Logistic (Logistic^{log} specification from Table 2. These refer to a logistic function applied to a linear combination of predictor variables in levels (logs). Observations are quarterly, by stock, conditioning on two or more institutional owners. The line represents an identity mapping.

Panel A. Estimated with logs on logs; predicted log value then translated to levels (for comparability)



Panel B. Estimated with a logistic function of a linear combination of predictor variables (Logistic)



Panel C. Specification is a logistic function of a linear combination of predictor variables (Logistic^{log})

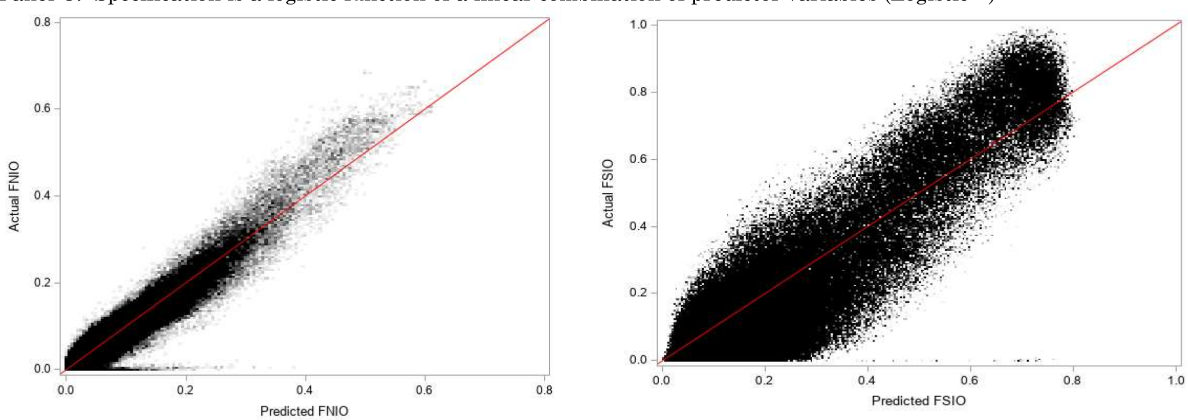


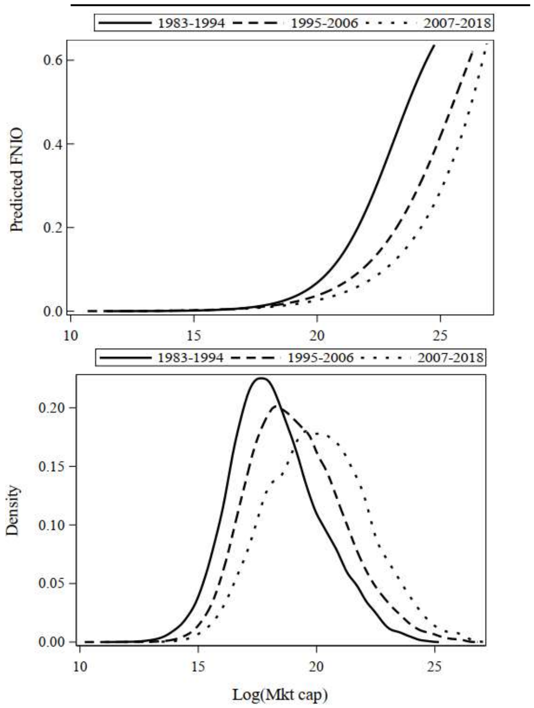
Figure 4

Graphical representation of specifications for predicted IO, 1983-2018

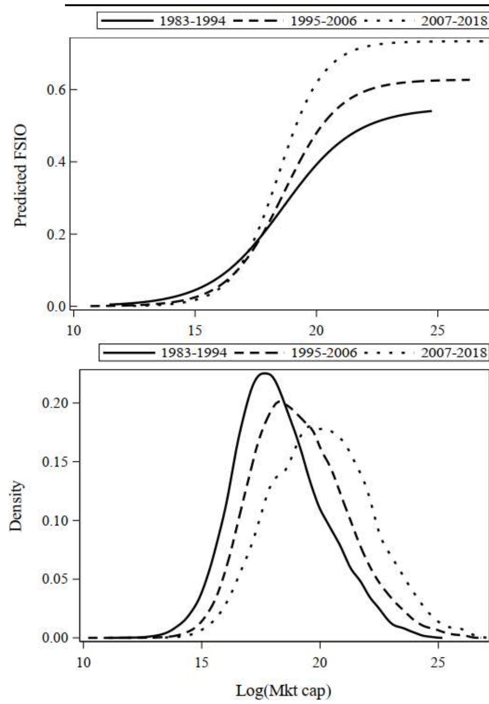
The first row on panel A and B present the functional form for predicted FNIO and FSIO from Logistic$^{\log}$ specification as in Table 2, except that here we use only one input (market capitalization) for graphing purposes. The second row on panel A and B also graph the density of log (Mkt cap.) for our sample of stocks. In each chart of Panel A, the functional form and density are mapped out three times, corresponding to 12-year periods ending in 1994, 2006, and 2018. Charts on the left (right) use FNIO (FSIO) of stocks. In each chart of Panel B, the functional form and density mapped out three times, corresponding to the first, third, and fifth quintile of institutions, sorted on EUM. Charts on the left show results for institutions-level (13F) holdings and charts on the right show results for portfolio-level (mutual funds) holdings.

Panel A: Predicted institutional ownership using Logistic$^{\mathrm{Log}}$ -by period

FNIO

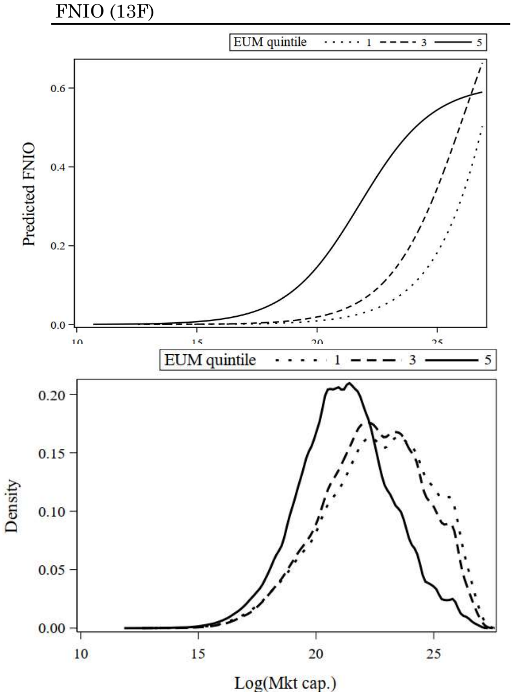


FSIO



Panel B: Predicted institutional ownership using Logistic$^{\mathrm{Log}}$ -by EUM quintile

FNIO (13F)



FNIO (mutual funds)

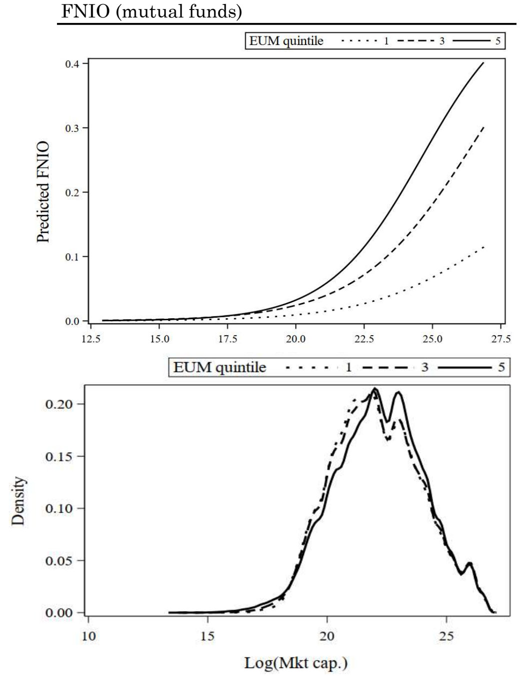


Figure 5

Institutional ownership by ventiles of market capitalization, 1983-2018

Each of the first three rows of charts corresponds to a 12 year period of the 13F sample. The fourth row corresponds to mutual fund holdings taken from the CRSP dataset, over the period 2011-2018. Panel A (B) presents the log of mean and median FNIO (FSIO) within each ventile of stocks sorted on the market capitalization. FNIO refers to the fractional number of institutional owners and FSIO refers to the fractional shares of institutional ownership. The solid line is the holdings of institutions in the largest equity under management (EUM) quintile; the dashed line refers to the third EUM quintile, and the dotted line refers to the smallest EUM quintile. Medians and Means are computed each quarter within ventiles of market capitalization, then averaged across the 12 years in the indicated period.

Panel A. FNIO

Panel B. FSIO

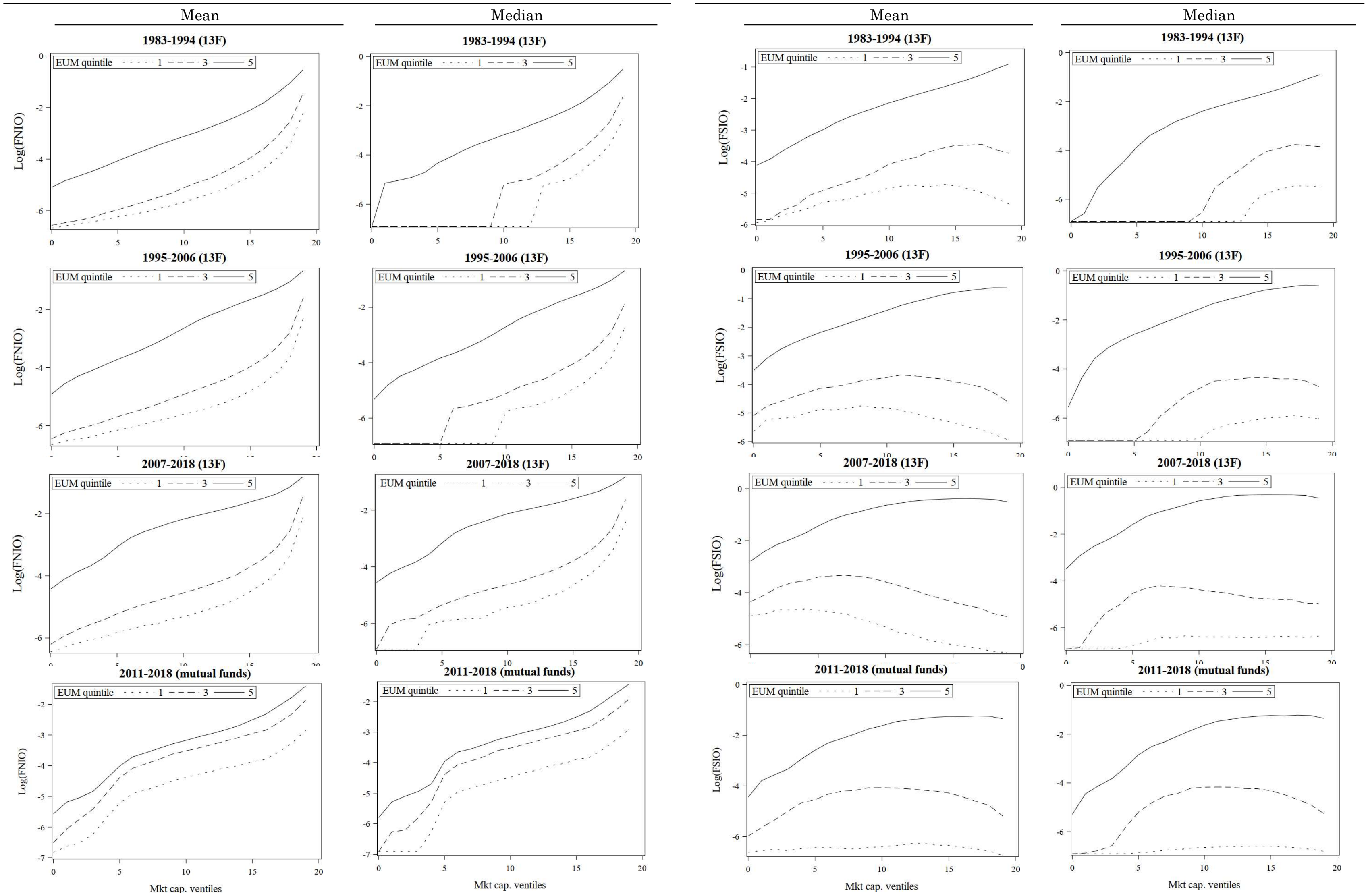
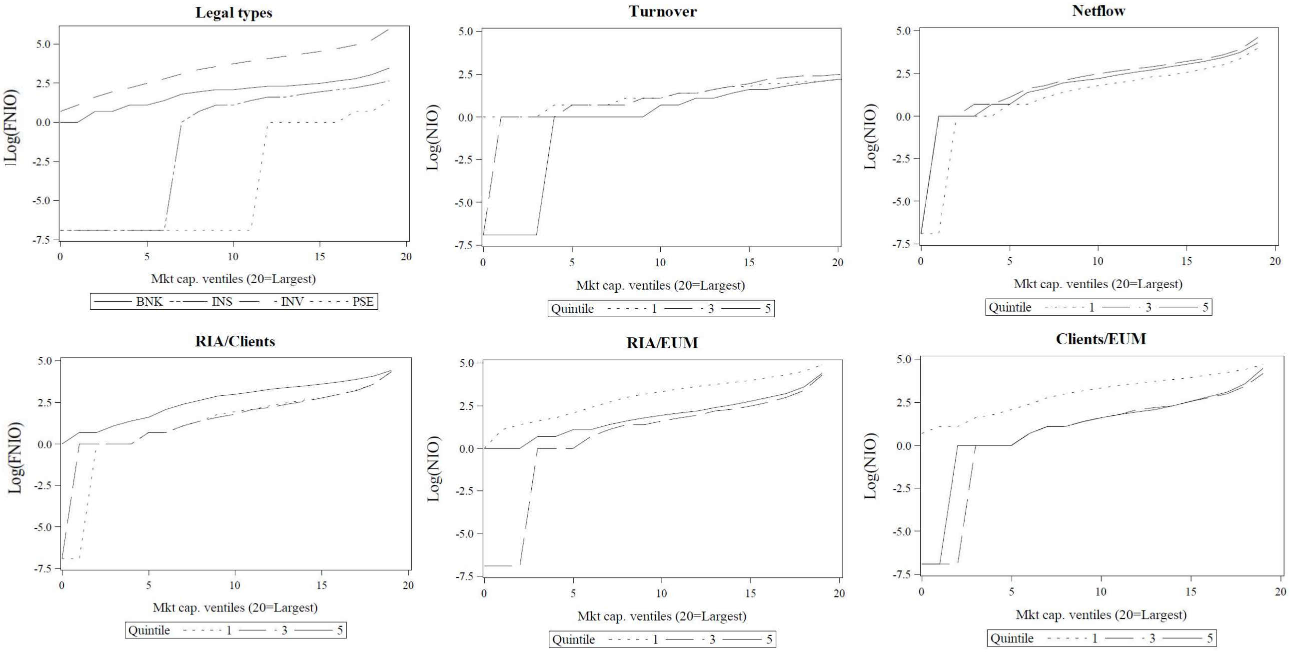


Figure 6

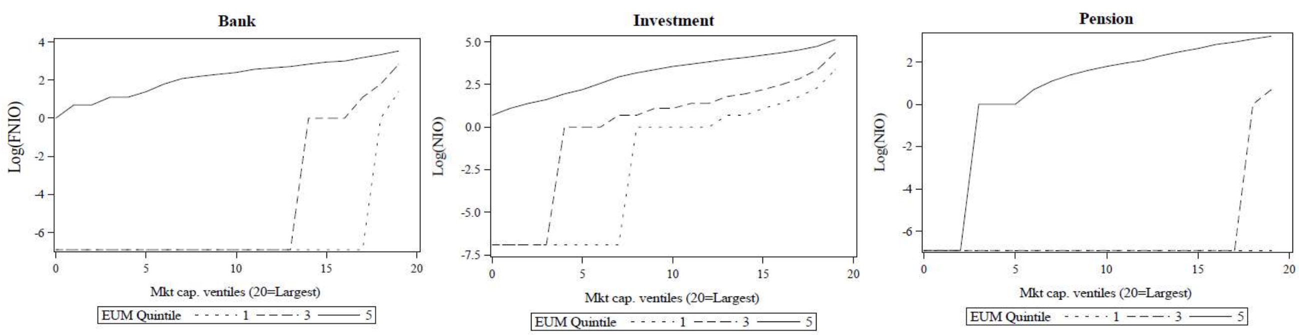
FNIO by ventiles of market capitalization and institutions characteristics, 1983-2018

These figures are constructed similarly to Figure 5, but report only on fractional number of institutional owners (FNIO) for subsets of institutions. Panel A correspond to institution type (banks BNK; insurance INS; investment advisers INV; and pensions and endowments PSE) and characteristics (turnover, net flow, and personnel). Turnover is the minimum of a buys or sells during the quarter divided by the average beginning and ending equity under management (EUM). Net flow is the percentage change in EUM minus the return on the beginning of quarter portfolio. Both are averaged and ranked into quintiles annually. Panel B details institution types by further ranking into terciles of EUM annually. Panel C corresponds to client type. Individuals include high net worth; pooled invetment vehicles includes mutual funds and commingled seperate accounts.

Panel A. FNIO by institution type and characteristics



Panel B. FNIO by institution type and size (EUM)



Panel C. Institutions by clientele

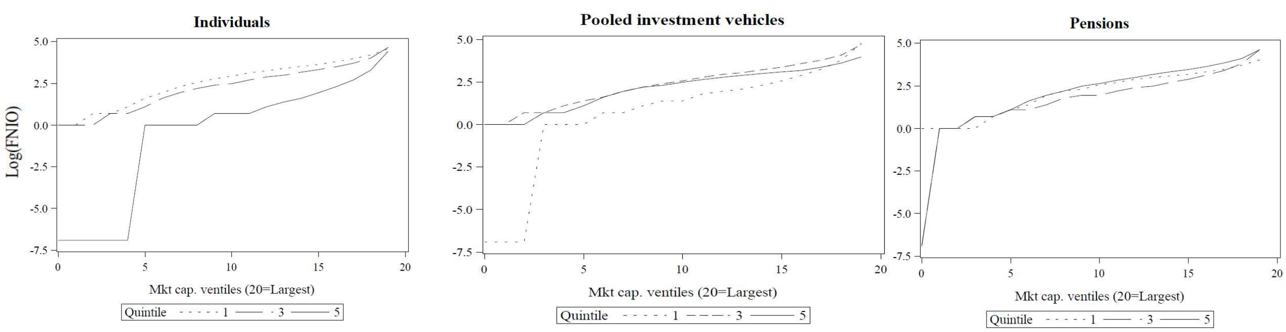
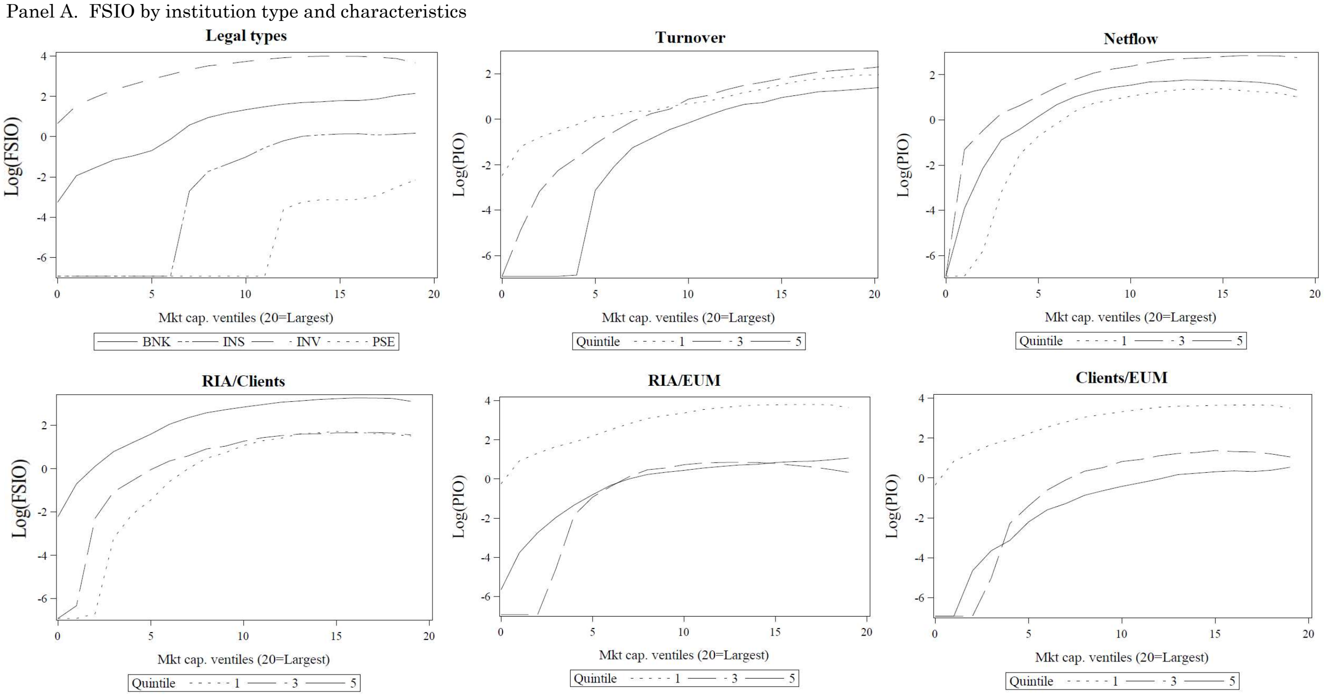


Figure 7

FSIO by ventiles of market capitalization and institutions characteristics, 1983-2018

These figures are constructed similarly to Figure 6, but report only on the fractional shares of institutional owners (FSIO) for subsets of institutions. Panel A correspond to institution type (banks; insurance; investment advisers; and pensions and endowments) and characteristics (turnover, net flow, and personnel). Turnover is the minimum of a buys or sells during the quarter divided by the average beginning and ending equity under management (EUM). Net flow is the percentage change in EUM minus the return on the beginning of quarter portfolio. Both are averaged and ranked into quintiles annually. Panel B corresponds to client type. Individuals include high net worth; pooled investment vehicles includes mutual funds and commingled separate accounts.

Panel A. FSIO by institution type and characteristics



Panel B. Institutions by clientele

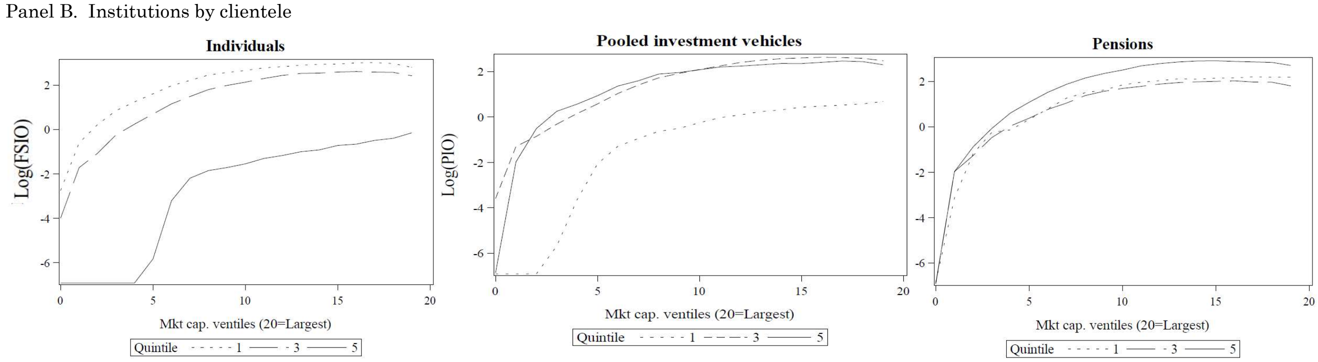


Table 1

Summary statistics, 1983 - 2018

This table presents medians (except for number and total) for stocks (Panel A) and institutions (Panel B). Columns labeled Q# refer to equity under management (EUM) quintiles. Panel C presents medians across all stocks held by institutions in the indicated EUM quintile. Held means more than one institutional owner. Each statistic is presented in three rows corresponding to 12-year periods ending in 1994, 2006, and 2018 (row heading just once). Medians are computed each quarter using only observations as indicated in the column heading, then averaged over the indicated period. $Turn^{MSCI}$ is the MSCI measure of turnover (see text). NIO is the number of institutional owners. FNIO refers to the fractional number of institutional owners and FSIO refers to the fractional shares of institutional ownership. $Capacity^{Hld}$ ($Capacity^{Trd}$) is the median stock's capitalization (Average 10-day Volume) divided by the median institution's EUM (the min subscript refers to over the previous year).

Panel A: Stocks

		All	Held
Number Stocks	< 1995	5,936	4,750
	1995 - 2007	6,059	5,640
	2007 - 2019	3,939	3,722
Total Mkt. cap ($B)		2,797	2,777
		11,400	11,368
		18,296	18,071
Mkt. cap ($M)		44	72
		177	200
		516	562
$Turn^{MSCI}$		0.03	0.05
		0.12	0.13
		0.23	0.24
NIO		10	14
		32	36
		85	91
FNIO (in %)		1.08	1.67
		1.78	2.01
		2.70	2.90
FSIO (in %)		13	19
		30	33
		57	60
$Capacity^{Hld}$		0.13	0.22
		0.56	0.62
		2.32	2.52
$Capacity^{Trd}$		0.11	0.23
		1.41	1.62
		9.56	10.77
$Capacity^{Trd}_{min}$		0.03	0.07
		0.61	0.70
		5.20	5.95

Panel B: Institutions (insts.)

	All	Q1	Q2-4	Q5
Number insts.	856	171	514	171
	1,705	341	1,023	341
	3,115	623	1,869	623
EUM all insts. ($B)	1,180	11	236	933
	5,968	22	489	5,456
	11,531	20	610	10,900
EUM, one inst. ($M)	332	72	332	3,352
	337	75	337	5,025
	224	32	224	3,368
Stocks per inst.	115	53	114	444
	94	44	93	422
	63	23	66	208

Panel C: Median characteristics for stocks in an institutions' portfolio

	Q1	Q2-4	Q5
NIO	72	46	16
	112	78	36
	152	118	93
FNIO (in %)	8.42	5.40	1.93
	6.68	4.56	2.12
	4.90	3.82	2.96
FSIO (in %)	42	38	21
	56	51	34
	72	68	60
$Capacity^{Hld}$	1.86	0.99	0.26
	3.44	1.86	0.66
	7.17	4.05	2.58
$Capacity^{Trd}$	4.05	1.96	0.30
	17.01	7.79	1.75
	49.52	21.56	11.06
$Capacity^{Trd}_{min}$	1.79	0.78	0.09
	9.03	3.84	0.76
	29.27	12.31	6.15

Table 2

Regression specification search:
R-squared from regression of institutional ownership on stock characteristics, 1983-2018

This table presents the R-squared from regressions of a variety of specifications of institutional ownership on a variety of specifications of stock characteristics. In Panel A, observations are panel (672k) including all stocks held by more than one institution. Dependent variables are the level and log of FNIO (FSIO). Capacity regressors are $\text{Capacity}^{\text{Hld}}$, $\text{Capacity}^{\text{Trd}}$, and $\text{Capacity}^{\text{Trd}}_{\text{min}}$ as defined in Table 1. The control variables are categorized into three groups of Index dummies (S&P 500, Russell 1000, and Russell 2000), Markets (price, beta, momentum, and volatility), and accounting Fundamentals (Firm age, B/M ratio, asset growth, and ROA). Column *All* provides R-squared for a regression including *Capacity* and all control variables. Column 'NIO' replaces FNIO with NIO as dependent variables and reports the R-squared of regressions. Specifications using the logistic function (i.e., regressions 3 and 4) are estimated with nonlinear least squares using Eq. (1). $\text{Logistic}^{\text{log}}$ uses logs of Capacity regressors as inputs to the logistic function. Panel B presents Max-rescaled from binary logit regression. The dependent variable (*Held*) is an indicator for a stock held by more than one institution. Observations are panel (754k obs.). Max-rescaled r-square uses likelihood-based pseudo-R-square and follows Nagelkerke's adjustment to reach a maximum value of 1. *%Concrd* reports percent concordant (i.e., rank-order correlations) of logistic regression. All regressions include time fixed effects, clustered by time, and weighted by one over the square root of the number of stocks in that calendar quarter. Both dependent and independent variables are standardized to have a standard deviation equals to one. Dependent variables are winzorized at the 0.1% tails.

Panel A. R-squared from continuous regressions of institutional ownership

	Model variables		Model specification		R-Squared	Control variables:				NIO
	Dependent	Regressors	Dependent	Regressors		Indices	Markets	Fundam.	All	All
1	FNIO	Capacity	Levels	Levels	32.6	73.4	40.8	44.4	74.0	86.3
2	FNIO	Capacity	Logs	Logs	85.0	86.0	85.7	85.7	86.7	87.5
3	FNIO	Capacity	Levels	Logistic	59.7	78.0	62.3	62.5	78.9	89.5
4	FNIO	Capacity	Levels	$\text{Logistic}^{\text{log}}$	90.7	91.7	91.2	91.4	92.4	92.6
1	FSIO	Capacity	Levels	Levels	20.5	47.3	32.2	23.7	48.7	
2	FSIO	Capacity	Logs	Logs	40.0	42.8	43.7	40.6	46.3	
3	FSIO	Capacity	Levels	Logistic	53.7	56.5	56.3	54.6	58.2	
4	FSIO	Capacity	Levels	$\text{Logistic}^{\text{log}}$	57.8	59.0	60.6	58.3	61.8	

Panel B. Max-rescaled from binary logit regression of institutional ownership

	Model variables		Model specification		R-Squared	Control variables:				%Concrd
	Dependent	Regressors	Dependent	Regressors		Indices	Markets	Fundam.	All	All
1	Held	Capacity	Binary	Levels	17.3	30.2	30.3	22.3	35.9	90.0
2	Held	Capacity	Binary	Logs	42.0	42.2	44.0	45.1	46.2	93.6

Table 3

Median institutional ownership within quintiles, 1983-2018

This table presents medians of institutional ownership within quintiles of stocks sorted on the indicated variable (each row) crossed with quintiles of institutions sorted on equity under management (EUM) (each column). FNIO refers to the fractional number of institutional owners and FSIO refers to the fractional shares of institutional ownership. Quintiles are formed independently by quarter; five is high. Mkt cap is the stock's market capitalization. Vol_{10} is the stock's median 10-day volume.

	Panel A. FNIO (%)					Panel B. FSIO (%)				
	Quintile of institutions by EUM					Quintile of institutions by EUM				
Stock quintiles:	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Mkt cap. - Q1	0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.1	2.9
Q2	0.0	0.2	0.3	0.4	2.1	0.0	0.2	0.4	1.4	12.4
Q3	0.3	0.4	0.5	0.8	5.3	0.0	0.2	0.6	2.4	28.0
Q4	0.6	0.8	1.2	2.3	12.4	0.1	0.4	1.0	3.4	42.7
Q5	2.1	3.4	5.0	8.6	31.1	0.2	0.6	1.3	3.6	50.8
Vol_{10} - Q1	0.0	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.1	3.3
Q2	0.0	0.2	0.3	0.4	2.1	0.0	0.1	0.3	1.1	11.9
Q3	0.3	0.4	0.5	0.8	5.3	0.0	0.2	0.5	2.2	27.0
Q4	0.6	0.8	1.2	2.3	12.4	0.1	0.4	0.9	3.3	41.7
Q5	2.1	3.4	4.9	8.5	30.9	0.2	0.6	1.3	3.8	52.1

Table 4

Summary statistics, 2000 - 2018 - Legal types, clients and employees

This table presents statistics relating to the sample of institutions from 2000 to 2018 (merged Forms 13F and ADV data). Values are computed each year then averaged across years. In Panel A institutions are divided into four types, with 'freq.' reporting the number of institutions in the merged dataset. EUM (AUM) is equity (assets) under management by an institution. Breadth% is the number of stocks held by the median institution as a fraction of all available stocks (CRSP NYSE, AMEX, Nasdaq). Position is the average investment size. %equity is EUM / AUM. In panel B, 'by Count' is the median across institutions of the number of clients in each category divided by the number of all clients for that institution, averaged across years. 'by Dollars' is similar but weighting by client dollars. In Panel C, Employees, RIAs, and clients are respectively the number of employees, registered investment advisors, and clients of the median institution, averaged across years. RIA_E is RIAs allocated to equity (RIAs * %equity). RIA_E/EUM, RIA_E/Stock, and RIA_E/Client are the number of RIA_E per million dollars of equity, per stock, and per client, respectively.

Panel A - Institution type and equity allocations

dataset:	Form 13F								From ADV			13F - ADV
	freq.	freq.%	EUM ($B)			Stocks per institution			AUM ($B)			% equity
			sum%	median	mean	median	breadth%	position ($M)	sum%	median	mean	
All	2215	100%	100%	0.25	3.76	73	1.65	3.65	100%	0.71	10.16	0.44
Inst. Category:												
Bank	56	2.9%	17.3%	0.7	23.9	309	7.2%	3.4	9.6%	1.3	42.0	0.49
Insurance	28	1.5%	4.9%	1.7	13.6	332	7.8%	5.5	3.5%	10.8	30.1	0.18
Investment	2113	94.8%	77.4%	0.2	3.1	70	1.6%	3.6	85.5%	0.7	9.2	0.44
Pensions.	13	0.7%	0.4%	0.7	2.2	98	2.2%	5.7	1.5%	4.9	19.8	0.27
Non	5	0.2%	0.0%	0.2	0.2	57	1.3%	5.2	1.3%	0.3	0.4	0.65

Panel B - Client types

	means			means - EUM weighted		
Client Type:	by Count	by Dollars	per	by Count	by Dollars	per
Individuals	51.2%	41.1%	0.80	27.2%	10.7%	0.39
Bank	1.1%	1.1%	0.94	1.9%	2.0%	1.04
Pooled Inv. vehicles	32.7%	40.7%	1.24	50.4%	61.4%	1.22
Pension	10.5%	8.4%	0.81	14.2%	7.3%	0.52
Insurance	1.1%	1.8%	1.62	2.8%	3.9%	1.42
Gov't and Sovereign	3.1%	3.2%	1.03	4.6%	4.6%	1.00

Panel C - Personnel

	mean	median	P25	P75
Employees	200	27	13	36
RIAs	84	14	7	30
Clients	48,368	134	27	349
RIA_E / EUM	0.134	0.02	0.01	0.04
RIA_E / Stocks	1.1	0.07	0.03	0.15
RIA_E / Clients	5.3	0.04	0.01	0.22
Clients / EUM	335	0.48	0.09	1.87

Table 5

Institutions' holding of low or high NIO stocks based on their characteristics, 2000 - 2018

This table presents statistics relating to the stocks held by institutions, sorting stocks by NIO (number of institutoinal owners) and sorting institutions by their characteristics. Stocks are sorted into quintiles based on their NIO, by year. The table then reports on institutions' holdings of stocks within each NIO quintile. Columns labeled 'by count' report on the mean fraction of an institutions' total count of positions in each NIO quintile (Q1 - Q5), and 'by dollar' reports on the mean fraction of EUM invested in each NIO quintile (Q1 - Q5). The first column is the median EUM, or median sort variable, for the indicated subset of institutions. Turnover is defined as the minimum of buys or sells during the quarter divided by the average beginning and ending equity under management (EUM). Net flow is the percentage change in EUM minus the return on the beginning of quarter portfolio. In all cases Q5 is high.

Panel A. Institutions partitioned by type

	median	by count					by dollar				
		Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Bank	$766 M	0.9%	3%	7%	12%	77%	0.1%	1%	2%	4%	93%
Insurance	$2492 M	0.5%	3%	8%	18%	71%	0.1%	1%	2%	7%	90%
Investment	$273 M	0.9%	4%	7%	14%	74%	0.4%	2%	5%	11%	81%
Pensions	$979 M	0.2%	1%	4%	11%	84%	0.0%	1%	2%	5%	93%

Panel B. Institutions partitioned by quintile of equity under management

Q1	$61 M	1.0%	4%	6%	10%	79%	0.5%	3%	5%	9%	82%
Q2	$137 M	1.0%	4%	6%	11%	78%	0.5%	2%	5%	10%	82%
Q3	$286 M	0.9%	4%	7%	12%	76%	0.3%	2%	5%	11%	81%
Q4	$780 M	0.8%	3%	8%	16%	72%	0.3%	2%	5%	14%	79%
Q5	$4379 M	0.7%	3%	9%	21%	66%	0.1%	1%	3%	12%	84%

Panel C. Institutions partitioned by quintile of turnover

Q1	2.4%	0.7%	2%	4%	8%	85%	0.2%	1%	2%	5%	91%
Q2	5.0%	0.8%	3%	5%	10%	82%	0.3%	1%	3%	7%	88%
Q3	8.2%	0.8%	3%	7%	14%	75%	0.3%	2%	4%	10%	84%
Q4	13.9%	1.0%	4%	9%	18%	68%	0.4%	2%	6%	14%	77%
Q5	29.1%	1.0%	5%	11%	21%	62%	0.5%	3%	8%	18%	71%

Panel D. Institutions partitioned by quintile of net flow

Q1	0.6%	0.8%	3%	6%	12%	79%	0.2%	1%	4%	9%	86%
Q2	1.8%	0.8%	3%	7%	13%	76%	0.3%	1%	4%	10%	84%
Q3	3.9%	0.9%	4%	8%	14%	73%	0.4%	2%	5%	11%	82%
Q4	7.9%	0.9%	4%	8%	16%	71%	0.4%	2%	6%	13%	79%
Q5	21.6%	1.1%	4%	9%	17%	68%	0.5%	3%	7%	14%	76%

Table 6
Institutions' holding of low or high NIO stocks based on clientele and RIAs, 2000 - 2018

This table presents statistics relating to the stocks held by institutions, sorting stocks by NIO (number of institutional owners) and sorting institutions by their characteristics. Stocks are sorted into quintiles based on their NIO, by year. The table then reports on institutions' holdings of stocks within each NIO quintile. Columns labeled 'by count' report on the mean fraction of an institutions' total count of positions in each NIO quintile (Q1 - Q5), and 'by dollar' reports on the mean fraction of EUM invested in each NIO quintile (Q1 - Q5). Panel A sorts institution's based on the number of clients of the indicated type. If clientele type is infrequent (e.g., bank clients), then the set of non-zero institutions is split into two equally populated groups (low and high). Otherwise, they are quartiles. Panel B sorts institutions based on RIA_E, defined as the number of registered investment advisers (RIAs) at the institution that we allocate to equity (RIA count times %equity as in Table 4). RIA_E/EUM is the number of RIA_E per $million EUM; RIA_E/Stock is per stock; and RIA_E/Client is per client.

Panel A - Institutions partitioned by clientele

			by count					by dollar				
Client category		Ratio	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
Individuals:	Q1	0.2%	1.3%	6%	12%	20%	59%	0.6%	4%	9%	17%	69%
	Q2	33.1%	0.8%	4%	9%	19%	67%	0.3%	1%	5%	15%	77%
	Q3	83.1%	0.7%	3%	5%	11%	80%	0.2%	1%	3%	8%	86%
	Q4	95.2%	0.6%	2%	3%	7%	86%	0.2%	1%	2%	5%	91%
Banks	low	0.0%	0.9%	4%	7%	14%	74%	0.4%	2%	5%	11%	80%
	high	7.6%	0.7%	3%	7%	15%	73%	0.2%	1%	3%	10%	86%
Investments	Q1	0.0%	0.5%	2%	3%	7%	87%	0.2%	1%	2%	5%	92%
	Q2	5.0%	0.7%	3%	6%	12%	77%	0.2%	1%	4%	10%	85%
	Q3	32.2%	0.9%	4%	9%	19%	66%	0.3%	2%	6%	15%	77%
	Q4	95.0%	1.5%	7%	13%	21%	57%	0.7%	4%	9%	18%	67%
Pensions	Q1	0.2%	1.2%	5%	10%	17%	65%	0.5%	3%	8%	14%	73%
	Q2	4.0%	0.7%	3%	6%	12%	77%	0.2%	1%	3%	8%	86%
	Q3	6.8%	0.7%	2%	5%	10%	81%	0.2%	1%	3%	8%	87%
	Q4	32.0%	0.6%	3%	7%	16%	73%	0.2%	1%	4%	12%	82%
Insurance	low	0.0%	0.9%	4%	8%	13%	73%	0.4%	2%	6%	11%	79%
	high	8.9%	0.7%	3%	8%	17%	70%	0.3%	1%	4%	11%	82%
Gov. & Sovr.	low	0.0%	0.9%	4%	7%	13%	74%	0.4%	2%	5%	11%	81%
	high	12.6%	0.6%	3%	7%	17%	71%	0.2%	1%	4%	12%	82%

Panel B - Institutions partitioned by registered investment advisers

RIA_e / EUM	Q1	0.00	0.8%	3%	9%	18%	68%	0.2%	1%	4%	12%	81%
	Q2	0.01	0.8%	4%	7%	14%	73%	0.3%	2%	5%	12%	79%
	Q3	0.03	0.8%	3%	6%	11%	77%	0.4%	2%	5%	10%	83%
	Q4	0.06	1.0%	4%	7%	12%	76%	0.5%	2%	5%	10%	82%
RIA_e / Stocks	Q1	0.02	0.8%	3%	7%	14%	74%	0.3%	2%	4%	9%	84%
	Q2	0.05	0.8%	3%	6%	12%	77%	0.3%	2%	4%	10%	83%
	Q3	0.10	0.8%	4%	7%	14%	73%	0.3%	2%	5%	12%	79%
	Q4	0.26	1.0%	4%	9%	16%	69%	0.4%	2%	6%	13%	78%
RIA_e / Clients	Q1	0.00	0.7%	3%	5%	10%	81%	0.3%	1%	3%	7%	88%
	Q2	0.02	0.6%	2%	5%	9%	82%	0.2%	1%	3%	7%	88%
	Q3	0.10	0.8%	4%	7%	15%	72%	0.4%	2%	6%	12%	79%
	Q4	0.54	1.0%	5%	11%	20%	61%	0.4%	3%	7%	16%	72%

Table 7a

Regression - Institutions characteristics and distribution of holdings, 2000 - 2018

This table details the effect of clientele, implementation, information acquisition capacity, and legal type. The dependent variables are Q1-2, Q3-4, and Q5 for regressions 1 and 2. In Panel A, Q1-2 (Q3-4) is the fraction of stocks invested by count in quintiles 1 and 2 (3 and 4) of stocks sorted on the NIO for an institution. Q5 is likewise the fraction of stocks invested by count in quintiles 5 of stocks sorted on the NIO for an institution. Panel B paralles Panel A but uses the dollar fraction of EUM invested in quintiles 1-2, 3-4. and 5. Each column presents coefficient estimates from a separate OLS regression across 2000-2018. The independent variables are categorized into four groups. The clientele variables are the fraction of the client "by count" for each observation. Implementation variables include EUM, Turnover, and Netflow. EUM represents the sum of all equity under management by an institution. Turnover is Carhart turnover which uses the minimum of a total buys or sells divided by the EUM. NetFlow is a money inflow net of outflow divided by EUM. Info. acquisition includes RIA (Registered Investment Advisors) and RIA*EUM interactions. Legal type indicators are dummy variables. Observations in the regression are weighted by the one over the square root of the number of institutions in the observation year. Time fixed effects are included. T-statistics uses standard errors clustered by year.

	Panel A. by count						**Panel B. by dollar**					
Regression:	(1)			(2)			(1)			(2)		
DV:	Q1-2	Q3-4	Q5	Q1-2	Q3-4	Q5	Q1-2	Q3-4	Q5	Q1-2	Q3-4	Q5
Intercept	0.050	0.172	0.778	0.032	0.067	0.901	0.025	0.119	0.856	0.020	0.026	0.955
	7.52	4.18	16.50	3.19	2.02	21.11	5.00	3.49	22.28	3.06	0.84	26.81
<u>Clientele (by count):</u>												
Individuals	-0.006	-0.036	0.042	-0.009	-0.025	0.034	-0.003	-0.023	0.026	-0.005	-0.019	0.024
	-3.35	-2.62	2.76	-3.14	-2.19	2.42	-2.04	-2.21	2.24	-2.49	-1.94	2.09
Banks	0.000	-0.001	0.001	0.000	-0.002	0.002	-0.001	-0.004	0.005	0.000	0.000	0.000
	-0.53	-0.35	0.40	-0.24	-0.76	0.61	-0.91	-1.41	1.34	0.62	-0.04	-0.11
Investments	0.019	0.062	-0.082	0.021	0.046	-0.066	0.013	0.061	-0.075	0.016	0.055	-0.071
	6.79	4.66	-5.17	5.23	4.12	-4.54	5.92	5.45	-5.72	5.14	5.21	-5.38
Pensions	-0.003	0.016	-0.013	-0.002	0.011	-0.009	-0.002	0.011	-0.009	0.000	0.014	-0.014
	-2.30	2.56	-1.83	-1.20	2.05	-1.33	-2.21	2.17	-1.52	-0.02	3.08	-2.48
Insurance	0.000	-0.001	0.001	0.001	-0.003	0.002	0.001	-0.002	0.001	0.002	0.000	-0.002
	0.48	-0.43	0.21	0.74	-1.12	0.63	1.33	-0.79	0.36	2.86	0.17	-0.83
Government & Sovr.	-0.002	0.009	-0.008	-0.002	0.005	-0.003	-0.002	0.006	-0.005	0.000	0.007	-0.007
	-3.04	2.32	-1.71	-2.16	1.37	-0.75	-3.99	1.83	-1.28	-0.79	2.35	-2.02
<u>Implementation:</u>												
Log(EUM)				-0.005	0.040	-0.035				-0.012	-0.011	0.023
				-6.36	23.50	-14.96				-14.25	-6.75	12.81
Turnover				-0.007	0.033	-0.027				-0.004	0.023	-0.018
				-4.34	15.42	-7.87				-3.60	7.97	-4.66
NetFlow				-0.001	-0.001	0.001				-0.001	-0.001	0.002
				-3.37	-1.57	2.22				-3.21	-2.40	2.66
<u>Info. acquisition:</u>												
RIA				0.000	0.004	-0.004				0.000	-0.003	0.002
				0.11	5.06	-3.65				1.39	-6.75	4.91
RIA *Log(EUM)				0.006	0.006	-0.012				0.001	0.000	-0.001
				9.91	3.29	-5.22				3.24	-0.07	-1.01
<u>Legal Type:</u>												
Investment dummy				0.025	0.047	-0.072				0.015	0.082	-0.098
				6.24	3.33	-4.16				6.47	6.14	-6.87
Bank dummy				0.020	0.011	-0.032				0.004	0.001	-0.005
				3.81	0.75	-1.61				1.46	0.08	-0.31
Pension dummy				-0.006	-0.045	0.051				0.003	-0.034	0.031
				-1.10	-2.90	2.57				0.84	-2.47	1.96
Insurance dummy				-0.002	0.022	-0.019				0.002	-0.002	0.000
				-0.54	0.98	-0.75				0.69	-0.14	0.00
R-Squared	8.61%	24.45%	24.33%	9.54%	29.78%	27.03%	5.65%	16.75%	17.40%	8.20%	18.53%	19.32%
N-Obs.	36,508	36,508	36,508	36,508	36,508	36,508	36,508	36,508	36,508	36,508	36,508	36,508
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes

Table 8

Regression - Institutions characteristics and distribution of holdings, 2011 - 2018

This table details the effect of clientele, implementation, information acquisition capacity, and legal type. The dependent variables are Q1-2, Q3-4, and Q5 for regressions 1 and 2. In Panel A, Q1-2 (Q3-4) is the fraction of stocks invested by count in quintiles 1 and 2 (3 and 4) of stocks sorted on the NIO for an institution. Q5 is likewise the fraction of stocks invested by count in quintiles 5 of stocks sorted on the NIO for an institution. Panel B paralles Panel A but uses the dollar fraction of EUM invested in quintiles 1-2, 3-4. and 5. Each column presents coefficient estimates from a separate OLS regression across 2000-2018. The independent variables are categorized into four groups. The clientele variables are the fraction of the client "**by dollar**" for each observation. Implementation variables include EUM, Turnover, and Netflow. EUM represents the sum of all equity under management by an institution. Turnover is Carhart turnover which uses the minimum of a total buys or sells divided by the EUM. NetFlow is a money inflow net of outflow divided by EUM. Info. acquisition includes RIA (Registered Investment Advisors) and RIA*EUM interactions. Legal type indicators are dummy variables. Observations in the regression are weighted by the one over the square root of the number of institutions in the observation year. Time fixed effects are included. T-statistics uses standard errors clustered by year.

	Panel A. by count						**Panel B. by dollar**					
Regression:	(1)			(2)			(1)			(2)		
DV:	Q1-2	Q3-4	Q5	Q1-2	Q3-4	Q5	Q1-2	Q3-4	Q5	Q1-2	Q3-4	Q5
Intercept	0.054	0.181	0.765	0.058	0.133	0.809	0.029	0.112	0.859	0.045	0.114	0.840
	9.18	8.78	31.86	8.43	10.80	45.28	6.84	10.50	66.37	7.20	5.20	31.45
Clientele (by dollar):												
Individuals	-0.009	-0.045	0.054	-0.016	-0.038	0.054	-0.005	-0.031	0.036	-0.012	-0.040	0.052
	-6.37	-7.59	8.58	-6.93	-7.41	7.84	-3.81	-9.65	9.56	-5.50	-6.54	6.64
Banks	-0.002	-0.003	0.005	-0.002	-0.004	0.006	-0.002	-0.008	0.010	-0.002	-0.005	0.007
	-7.78	-4.40	6.38	-7.55	-5.53	7.01	-6.18	-6.57	7.42	-4.50	-4.35	4.93
Investments	0.020	0.058	-0.078	0.028	0.056	-0.084	0.017	0.075	-0.091	0.021	0.071	-0.092
	8.62	12.96	-12.84	9.09	13.68	-13.26	7.30	19.98	-17.88	6.23	11.71	-10.51
Pensions	-0.002	0.010	-0.008	-0.002	0.013	-0.010	-0.003	0.012	-0.009	-0.002	0.014	-0.012
	-4.21	6.14	-5.14	-2.86	6.48	-5.21	-4.23	6.80	-5.54	-2.63	5.53	-4.39
Insurance	-0.002	-0.002	0.003	-0.002	-0.005	0.007	-0.001	-0.007	0.008	0.001	-0.003	0.003
	-3.05	-1.27	2.04	-2.36	-3.11	3.31	-1.24	-4.05	3.97	0.91	-1.85	1.31
Government & Sovr.	-0.001	0.016	-0.014	0.000	0.018	-0.018	-0.002	0.018	-0.016	0.000	0.020	-0.021
	-3.37	12.71	-9.60	-0.44	11.64	-9.11	-3.47	13.84	-9.51	0.43	13.84	-10.95
Implementation:												
Log(EUM)				-0.012	0.025	-0.013				-0.018	-0.028	0.046
				-15.65	11.62	-5.09				-14.32	-10.93	17.08
Turnover				-0.012	0.025	-0.012				-0.010	0.008	0.002
				-8.53	13.34	-4.06				-11.52	3.01	0.52
NetFlow				-0.001	-0.001	0.002				-0.001	-0.002	0.002
				-2.64	-2.51	2.64				-2.71	-1.90	2.19
Info. acquisition:												
RIA				0.001	0.006	-0.007				0.001	-0.001	0.000
				2.81	5.23	-4.56				2.79	-0.78	-0.18
RIA *Log(EUM)				0.007	0.006	-0.013				0.001	0.000	-0.001
				9.14	2.97	-4.72				3.44	0.70	-1.50
Legal Type:												
Investment dummy				0.014	-0.007	-0.007				0.009	0.025	-0.035
				4.24	-1.02	-0.83				4.19	1.72	-2.23
Bank dummy				0.004	-0.035	0.031				-0.003	-0.056	0.059
				1.00	-4.52	3.04				-1.04	-3.57	3.39
Pension dummy				-0.017	-0.098	0.114				-0.001	-0.083	0.084
				-3.55	-10.84	9.79				-0.30	-7.46	6.24
Insurance dummy				0.003	0.028	-0.031				0.008	-0.021	0.013
				0.54	4.74	-3.59				1.76	-1.49	0.77
R-Squared	10.41%	30.72%	30.65%	12.49%	32.82%	31.26%	6.74%	22.25%	22.77%	10.64%	23.66%	25.18%
N-Obs.	18,295	18,295	18,295	18,295	18,295	18,295	18,295	18,295	18,295	18,295	18,295	18,295
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes