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Abstract

Large institutional investors own an increasing share of equity markets in the U.S. The implications of this development for financial markets are still unclear. The paper presents novel empirical evidence that ownership by large institutions predicts higher volatility and greater noise in stock prices, as well as more fragility at times of crisis. Evidence from a natural experiment suggests a causal interpretation of this effect. When studying the channel, we find that large institutional investors exhibit traits of granularity, i.e. subunits within a firm display correlated behavior, which reduces diversification of idiosyncratic shocks.

JEL Classification: G01, G12, G23

Keywords: institutional investors, Concentration, granularity, fire sales, liquidity

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The Granular Nature of Large Institutional Investors

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1 Introduction

The recent decades have witnessed the rise of large institutional players in financial markets. Since 1980, the top 10 institutional investors have quadrupled their holdings in U.S. stocks. As of December 2016, the largest institutional investor oversaw 6.3% of the total equity assets, and the top 10 investors managed 26.5% of these assets. Observing these trends, regulators have expressed concerns about systemic risks that could result from the high concentration of assets under a few large actors. The main threat is that institutional investors, when experiencing redemptions, liquidate their portfolios and destabilize asset prices, propagating the effect to other investors' balance sheets.[1] Any potential implications of large institutional investors on the prices of the securities they hold remain unclear and unexplored.

Theoretical arguments suggest that large institutions should impact stock prices more than small institutions. Gabaix (2011) posits that large market players are "granular," i.e., shocks to these agents are not easily diversified when aggregating across units and are reflected in aggregate market outcomes. In particular, aggregate fluctuations can result from firm-level shocks if the distribution of firms is fat-tailed. Applying this notion to financial markets, Gabaix, Gopikrishnan, Plerou, and Stanley (2006) suggest that the trades of large investors can explain excess volatility.

Drawing inspiration from this theory, our empirical contribution is twofold. First, we show that ownership by large institutions increases volatility in the underlying securities, and that this increase reflects a rise of noise in stock prices. We can attribute a causal interpretation to this finding thanks to the natural experiment resulting from the merger of two large institutions. Moreover, we show that during times of market turmoil, stocks with higher ownership by large institutions display significantly larger price drops. This finding is relevant for regulators who are concerned about financial stability.

Second, when studying the channels behind these effects, we find empirical evidence supporting the view that large institutions are granular, i.e. behavior within the subunits of a large firm displays some correlation that limits internal diversification and exacerbates market impact.

[1] The Office of Financial Research (2013) identifies redemption risk as a major vulnerability of asset managers, and points to the fire sale channel as a source of systemic risk. Relatedly, a recent Financial Stability Board publication (2015) remarks that, although research studying market contagion is abundant, a gap exists in the study of the potential effect of large individual organizations.

In particular, capital flows and trading strategies are more correlated across different entities within the same institution than across independent managers. We interpret this evidence as the outcome of centralized functions, such as marketing, research, and risk management, as well as of a unique corporate identity that guides managers' decision and investors' responses. These results can explain why large institutions have a bigger impact on asset prices than a collection of smaller independent entities.

In more detail, we start from the hypothesis that large investors' trading activity leads to more intense price pressure, which in turn translates into higher stock price volatility. We confirm this prediction by showing a significant relation between ownership by top institutions and stock-level volatility. The economic magnitude of this effect grows over time, coinciding with the rise of importance of large institutions in financial markets. Towards the end of the sample the effect is economically large: a one-standard deviation increase in the largest ten institutions' ownership is associated with 16% of a standard deviation increase in volatility. While our main tests focus on daily volatility, the effect is also present at lower frequencies (weekly, monthly, quarterly), making it relevant for long-term investors as well.

To address potential endogeneity of institutional ownership, we exploit a natural experiment originating from the merger of two large institutional investors in 2009, which is arguably an exogenous event relative to the determinants of volatility. Securities in the portfolio of the smaller institution are, after the merger, owned by the top institution in the market. We expect therefore their volatility to increase. Indeed, we find a significant increase in post-merger volatility as a function of pre-merger ownership by the smaller firm (the treatment variable).

One might speculate that the increase in volatility that we identify is a desirable outcome of institutional ownership. For example, large institutions could encourage information production and faster price discovery. To shed light on this issue, we investigate whether large institutions are associated with more efficient prices. In fact, focusing on daily return autocorrelation, we find that stocks with higher ownership by top institutions display more negatively autocorrelated returns. This evidence is consistent with the idea that large institutions impound liquidity shocks into prices, which then revert, and lead to noisier prices.

Next, we directly address the regulatory concerns and study the effect of large institutional investors on stock prices during periods of market turmoil. Given our conjecture that large investors influence asset prices through a more intense demand for liquidity, we expect the prices of the stocks that they own to be more fragile when aggregate liquidity is low. Accordingly, we find that in turmoil periods, stocks with higher ownership by large institutions experience significantly lower returns, while no effect on the level of returns is present in normal times.

In the second part of the paper, we study the potential drivers of the previous findings. Focusing on the granularity of large institutional investors, we ask whether different units within a large firm display more correlated behavior than independent asset managers. The within-firm correlation, in turn, would prevent the diversification of idiosyncratic shocks, causing a larger impact of these shocks on asset prices. We investigate several channels. First, intuitive arguments suggest that the various asset managers in the same institution may experience more correlated capital flows than independent entities. For example, institutions typically cultivate a brand name, and therefore affiliated entities are perceived as sharing the destiny of the broader family. Similarly, distribution policies and cross-selling practices (e.g., funds that are offered in company pension schemes) may increase flow correlation. Consistent with this conjecture, we find that the correlation of flows of mutual funds within the same family is significantly higher than that of independent funds.

Second, investment choices may be correlated for asset managers who operate under the same institution. In particular, institutions often rely on a centralized research division that generates investment views that inform trading decisions across the family. Thus, even though different asset managers have leeway in their portfolio allocation, their behavior may display abnormal correlation due to the family-wide investment directions. Two pieces of evidence support this conjecture. First, portfolio rebalancing trades are also significantly more correlated for mutual funds in the same family. Second, entities within the same group trade on a smaller set of stocks relative to the investment universe of independent firms, which is consistent with an overlap in investment strategies within the same family.

Finally, we show that trades by large institutions are bigger than those of a synthetic control group made of independent firms with the same total assets as the large institution. This evidence is also consistent with the granularity of large institutional investors, as it suggests that different units within the same firm are more likely to trade in the same direction, so that their trades do not cancel out. This finding can explain why the trading intensity on stocks owned by large institutions is more pronounced and the prices of these securities are more volatile, noisier, and more fragile.

Our paper relates to a body of economic literature studying the impact of granularity in several contexts. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Kelly, Lustig, and Van Nieuwerburgh (2013) study the effects on supply chains, and Blank, Buch, and Neugebauer (2009) and Bremus, Buch, Russ, and Schnitzer (2013) study the effects of granularly large banks on the banking industry. Corsetti, Dasgupta, Morris, and Shin (2004) develop a model that explains the impact of one large trader on the behavior of small traders.

In finance, we relate to a literature showing the impact of institutional investors on asset prices. Sias (1996) and Bushee and Noe (2000) find evidence that increases in institutional ownership are accompanied by a rise in stock volatility. Our novel contribution is to identify large institutional investors as a separate and more important contributor to stock price volatility. Other papers establish that aggregate institutional ownership can affect the volatility and correlation of asset returns and liquidity (Greenwood and Thesmar 2011; Anton and Polk 2014). Our original contribution is to show that few large institutions can induce this effect. Koijen and Yogo (2015) estimate a structural model in which large institutional investors smooth their price impact and therefore have a muted effect on aggregate market volatility. Different from these authors, we provide direct reduced-form evidence on the effect of ownership structure on volatility.[2]

The paper proceeds as follows. Section 2 lays out our testable conjecture with the aid of a simple model. Section 3 describes the data. Section 4 explores the implications of large institutions for asset prices. Section 5 explores the channel. Section 6 concludes.

[2] We also relate to a literature studying demand- and supply-side drivers of market liquidity, inspired by the theory of Brunnermeier and Pedersen (2008). For example, Hameed, Kang, and Viswanathan (2010) and Aragon and Strahan (2012) identify a significant role of supply-side determinants, which lead to systematic liquidity dry-ups during market downturns. Karolyi, Lee, and Dijk (2012) and Kamara Lou and Sadka (2008) show that correlated demand for liquidity, proxied by commonality in institutional ownership and related trading volume, is a prominent factor. Koch, Ruenzi, and Starks (2016) show that correlated demand by mutual funds generates liquidity commonality. Our work identifies large institutions' trading activity as a novel demand-side determinant of liquidity shocks.

2 Hypothesis Development

To support our empirical analysis, we lay out a simple theoretical framework. In particular, starting from reduced form equations on the behavior of asset managers and the price setting mechanism in the market, we obtain an equation that illustrates a potential channel for the impact of granular asset managers on asset prices.[3]

We assume that the dollar demand of a stock that a manager submits to the market depends positively on the dollar size of the manager's portfolio. This reduced-form equation is the outcome of an optimization problem. The manager responds to publicly observable signals, such as earnings announcements, and to idiosyncratic institutional shocks, such as unexpected redemptions by the institution's clients. Formally, the market demand for stock i by manager k at time t is a function of the manager's investment in the stock in the prior period, labeled A_{ikt-1}:

$$\Delta A_{ikt} = a_t A_{ikt-1} + \eta_{kt} w_{ikt-1} f(A_{kt-1}), \tag{1}$$

where a_t is a common shock to all managers (e.g., driven by aggregate market news), with variance σ_a^2, and η_{kt} is an idiosyncratic component (e.g., driven by the institution's flows), with variance σ_η^2. The two components are uncorrelated. Also, η_{kt} is uncorrelated across managers. w_{ikt-1} is the weight of the stock in the institution's portfolio. Intuitively, if the manager does not hold the stock, idiosyncratic shocks, such as unexpected redemptions, do not affect the demand for the stock.

A_{kt-1} is the total size of the institution's portfolio. The function f mediates the effect of the size of the institution on the demand for the stock and it is such that $f \geq 0$, $f(0) = 0$, $f' > 0$, and $f'' \leq 0$. This function captures the extent of granularity of a given institution. If institutions are able to fully diversify idiosyncratic shock internally, i.e. the case in which $f = 0$, these shocks do not lead to a net demand for the stock from the institution. In this case, a large institution is closer to a collection of many independent firms that are exposed to demand shocks that cancel out and do not increase the net demand for the stock. At the other extreme, f is a linear function (i.e. $f'' =$

[3] We draw inspiration from Greenwood and Thesmar (2011), but we differ from their work in highlighting the effect of large institutional ownership as a distinct channel for price volatility. The authors, instead, focus on the correlation and volatility of fund flows across asset managers and the concentration in the ownership base of a given company. The structure of the theoretical framework is similar to that of Landier, Sraer, and Thesmar (2017), who study the concentration in the bank lending market. Similar reduced form formulations for investors' asset demands and price impact of trades are present in Gabaix, Gopikrishnan, Plerou, and Stanley (2006).

0) and institutions are fully granular. In this case, the idiosyncratic shock scales up proportionally with the size of the institution and it fully translates into demand for the stock.

The empirical evidence suggests that large institutions make efforts to smooth shocks internally by exchanging assets across funds within a family in off-market transactions (Gaspar, Massa, and Matos, 2006; Bhattacharya, Lee, and Pool, 2013). On the other hand, one can reasonably conjecture that the entities within the same large institutions experience correlated flows and implement correlated investment strategies. In other words, different entities within a large firm may be exposed to correlated shocks. If this is the case, one can reasonably conclude that, while the size of the shock may not grow linearly with the size of the institution, the reality is far from a situation in which shocks are fully diversified internally.

Based on models with asymmetric information (e.g. Kyle 1985) or risk averse market makers (e.g., Grossman and Miller 1988), we assume a reduced-form equation for the price impact of trading. Specifically,

$$R_{it} = \mu \sum_{k \epsilon K} \frac{\Delta A_{ikt}}{m_{it-1}} + e_{it} \, , \tag{2}$$

where m_{it-1} is the market capitalization of the stock at time $t-1$. e_{it} can be thought of as a fundamental shock to stock prices, with a variance-covariance matrix across stocks given by $\Sigma_e = \sigma_e^2(\rho J + (1-\rho)I)$, where J is a square matrix of ones and I is the identity matrix, and both matrices have size equal to the number K of managers in the market. To avoid unnecessarily complicating notation, we assume the price impact parameter μ is the same across stocks.

Combining equations (1) and (2), and assuming the K investors hold all the outstanding shares of stock i, so that $\sum_{k \epsilon K} A_{ikt-1} = m_{it-1}$, we derive the expression for the variance of stock returns:

$$Var(R_{it}) = \sigma_e^2 + \mu^2 \sigma_a^2 + \mu^2 \sigma_\eta^2 \sum_{k \epsilon K} \left(\frac{w_{ikt-1} f(A_{kt-1})}{m_{it-1}} \right)^2 . \tag{3}$$

Hence, the variance of returns has an idiosyncratic fundamental component, σ_e^2, a systematic component due to aggregate shocks driving institutional trades, $\mu^2 \sigma_a^2$, and a third component that depends on the shape of the function f and the structure of ownership. Because $w_{ikt-1} = \frac{A_{ikt-1}}{A_{kt-1}}$, if f is linear, the third term corresponds to the Herfindahl index of the managers' ownership shares in the company. Intuitively, if the stock ownership is more concentrated, the shocks of individual managers are a bigger fraction of the stock demand and are less easily diversified across managers. Hence, these shocks translate into stronger price pressure and higher variance (Greenwood and Thesmar, 2011).

To develop further intuition, we divide and multiply $f(A_{kt-1})$ by A_{kt-1} in Equation (3). Then, we can rewrite the stock price variance as

$$Var(R_{it}) = \sigma_e^2 + \mu^2\sigma_a^2 + \mu^2\sigma_\eta^2 \sum_{k \epsilon K} \left[\frac{A_{kt-1}}{M_{t-1}} \cdot \frac{f(A_{kt-1})}{A_{kt-1}} \cdot \frac{w_{ikt-1}}{q_{it-1}}\right]^2, \quad (4)$$

where $q_{it-1} = \frac{m_{it-1}}{M_{t-1}}$ is the weight of the stock in the market portfolio. The first term in brackets, $\frac{A_{kt-1}}{M_{t-1}}$, captures the size of an institution's equity portfolio relative to the stock market. Because of this term, return volatility depends on the extent of ownership by large firms. Intuitively, the more large institutions hold the stock, the greater the difficulty in diversifying idiosyncratic institutional shocks when they reach the market through institutional trades. The second term, $\frac{f(A_{kt-1})}{A_{kt-1}}$, attenuates the effect of institutional size, as a function of the concavity of f (i.e. the extent of granularity). Institutions that manage to diversify shocks internally, even if they are very large, do not have a large price impact and, consequently, they have a smaller effect on volatility. Finally, the third term, $\frac{w_{ikt-1}}{q_{it-1}}$, modulates the impact of a given institution on return volatility as a function of the holdings of that stock. For example, if a stock is not part of an institution's portfolio, that is, $w_{ikt-1} = 0$, that institution does not contribute to return volatility.

Let us consider the case of maximum granularity, i.e. when the function f is linear. Further, let us set $\frac{w_{ikt-1}}{q_{it-1}} = 1$ for ease of intuition. In this scenario, the variance depends exactly on the Herfindahl index of the asset management industry. In such a case, when an asset management sector is populated by atomistic managers, each owning a very small portfolio (i.e., $A_{kt-1} \approx 0$ for all managers k), the effect on volatility of institutional shocks disappears. On the other extreme, if only two large institutions are present in the market, the effect of those institutions on return volatility is maximized.[4]

Hence, Equation (4) contains the main testable prediction of the model:

Stock return volatility is positively related to the amount of ownership of large asset managers in that stock. The magnitude of this effect depends on the extent of granularity of large institutions, i.e. the extent to which idiosyncratic shocks to an institution are not diversified internally.

In the next section, we study the effect of large institutions on volatility. Then, in the following part of the paper, we investigate the channel. In particular, we study the factors that may limit internal diversification of shocks within large institutions.

3 Data Description

To construct our sample, we use institutional ownership data from the first quarter of 1980 to the fourth quarter of 2016 from Thomson-Reuters and the original SEC 13F filings.[5,6]

We identify the largest institutional investors in each quarter based on a rolling four-quarter average of the rankings of their aggregate equity holdings. At the top of the ranking, we find a firm that held its position almost uninterruptedly since 1990 to the end of the sample, experiencing a change of denomination of the reporting entity in 1997 and a merger in 2009, which we will further discuss below. Overall, our sample contains 40 unique institutions that fell within the top 10 institutions at some point during our sample period. They hold an average of $169 billion

[4] In fact, the effect on variance would be maximized with only one institution owning the entire market. This is not a realistic scenario because in this case the institution would not find a trading counterparty and there would be no foundation for equation (2), which assumes that price concessions derive from trading activity.

[5] The 13F filings require all institutions with investment discretion over $100 million or more of U.S. equity assets at the end of the year to provide detailed quarterly reports of their long holdings in these qualified securities in the next year. See Ben-David, Franzoni, and Moussawi (2012) for institutional details regarding 13F data and an overview of the Thomson-Reuters Institutional Ownership database.

[6] In our preliminary analysis, we noticed that the Thomson-Reuters' data exhibit a substantial increase in stale holdings reports and in the number of dropped institutions, starting in 2013. For example, we found that in 2015 Thomson-Reuters' data underreports institutional ownership in the 13F filings by about 10% due to omissions of institutions and securities. In the Internet Appendix, we describe an alternative data collection approach that overcomes these limitations and make it available to other researchers.

(inflation-adjusted to the end of 2016) in assets in a given quarter of our sample. The Appendix provides a list of all institutions that appear in the top 10 ranking during our sample period.

We measure large institutional holdings as aggregated ownership by subsets of large institutions, specifically the top 3, top 5, top 7, and top 10 institutional investors. We use all stocks in the Center for Research in Security Prices (CRSP) universe, regardless of whether they are held by the largest institutional investors. We use data from CRSP and Compustat to construct other stock-level variables. Because the main variables from the 13F filings are at a quarterly frequency, we construct all other variables at a quarterly frequency. Table 1, Panel A, provides summary statistics for our sample of institutional investors. The top 10 institutional investors hold on average 8.1% of the outstanding shares of a given stock, with a standard deviation of ownership of 9%. Ownership of the average stock decreases for the combined top 11 through top 20 institutions and beyond. The top 30 through top 50 institutions together hold 2.7% of the shares outstanding of the average stock in our sample. Ownership by large institutions can be compared to aggregate institutional ownership. We observe that for the average stock in our sample, institutional investors own 38% of its shares (*Ownership by all institutions*).[7]

Figure 1 plots the time series of the percentage of holdings of large institutions over our sample period. We include the holdings of the largest institutional investor as well as those of the groups of the top 3, 5, 7, and 10 largest investors. We observe that the percentage of total shares outstanding held by large institutions in an average US common stock is increasing over time. For example, the largest institution in the economy more than quadruples its holdings from 1.4% of the equity market at the beginning of the sample (1980) to 6.3% at the end of the sample (2016). Similarly, the largest 10 institutions own 5.6% at the beginning of the sample and 26.5% at the end. Over the same period, ownership by all institutions roughly doubles. Comparing this trend to the faster growth of large institutions suggests that ownership has become more concentrated over time. The Internet Appendix provides a detailed description of the variables we use in the study.

[7] We note the maximum value of *Ownership by all institutions* is 1.27. Indeed, institutional ownership might be above 100%. This rare situation occurs when shares that have been short sold are double-counted. Lewellen (2011) discusses these situations and concludes that they do not represent data errors, but rather are the result of short selling.

4 The Effect of Large Institutions on Asset Prices

4.1 Volatility

The main testable prediction from Section 2 is that large institution have a larger impact on stock volatility than a collection of smaller independent managers in case of granularity. To study the effect of large institutions on volatility, we start from a simple specification:

$$Volatility_{iq} = Top\ Inst\ Ownership_{i,q-1} + Controls_{i,q-1} + Time\ FE_q + Stock\ FE_i + \varepsilon_{iq}. \quad (5)$$

We estimate equation (5) using ordinary least squares (OLS) regressions. The variables are measured quarterly at the stock level. The dependent variable is stock volatility measured over the calendar quarter. Top Institutional Ownership is the fraction of shares outstanding collectively held by the top 3, 5, 7, and 10 institutions (*Top inst. ownership*). We include the following controls: lagged *log(market cap),* lagged *book-to-market* ratio, lagged *6-month past returns*, lagged inverse price ratio (*1/price*), lagged *Amihud illiquidity* ratio (Amihud, 2002), and lagged total *ownership by "middle" institutions* (which reflects ownership by all institutions ranked below the ones at the top, excluding those included among the bottom institutions, see next). We also add a variable that measures the lagged total *ownership by bottom institutions* whose aggregate equity holdings sum up to that of the largest 10 institutions. Using this variable, we can verify whether the effect of interest originates from the size of assets under management, irrespective of whether the assets are managed by top institutions. Lastly, our specifications include stock and time (at the quarterly frequency) fixed effects. Standard errors are double-clustered at the stock and quarter level throughout our analysis, unless otherwise specified.

The estimates are presented in Table 2, Panel A. We note that up to the 30^{th} largest institution, the positive relation between ownership by large institutions and stock volatility is statistically significant. The magnitude decreases substantially for institutional investors ranked 21^{st} to 30^{th}, and it is indistinguishable from zero for institutional investors ranked 31^{st} to 50^{th}. Furthermore, the effect of ownership by the bottom institutional investors with the same total size as the top 10 institutions is negative, strengthening the view that only large investors play a role in increasing volatility.

We can provide the economic magnitude of our result. Focusing on the top 10 investors and using the summary statistics in Table 1, a one-standard deviation increase in their ownership is associated with an increase in volatility of 3.33% of a standard deviation (0.945*0.090/2.55). In the same specification, ownership by middle institutions has a magnitude of only 0.7% of a standard deviation (0.082*0.228/2.55). Hence, the slope for large institutions is 4.5 times as large.[8]

Greenwood and Thesmar's (2011) construct a fragility measure that captures the effective concentration of ownership in a stock, weighted by the volatility and correlation of the trading needs of its investors. This variable accounts for large (i.e., concentrated) ownership stakes by institutional investors, irrespective of the size of the institution. Instead, we focus our attention on ownership by large institutions, as a distinct channel from large stakes by institutions of any size. We find a high correlation (54%) between Greenwood and Thesmar's (2011) fragility measure and ownership by the top 10 institutions. Therefore, a test of whether the two effects can coexist in the data is interesting. In Table 2, Panel B, we add Greenwood and Thesmar's (2011) measure to our main regression model. We again find that the coefficient on large institutional ownership is positive and statistically significant. We conclude that ownership by large institutions and fragility capture two partly independent empirical phenomena.

We next carry out subsample analysis to determine whether the effect of large institutions on volatility changes over time. The increasing concentration in stock ownership implies that finding trading counterparties for large trades is more difficult in recent times. Keeping other market characteristics constant, the same amount of trading by a large institution should lead to bigger price movements in recent times. On the other hand, stock market liquidity has significantly improved over our sample period. It remains, therefore, an empirical question whether the impact of large institutions on stock prices increases over time.

We split our sample into three periods: 1980-1990, 1991-2003, and 2004-2016. Corresponding results are shown in Table 3, Panels A, B, and C, respectively. We find that in the

[8] In the specifications focusing on the top institutions (up to the top 10), the magnitude of the slope for top institutions is larger than the slope for the "middle" ones by at least 42% and on average 205%. Therefore, the effect of top institutions is economically more important than the effect of "middle" institutions by at least an order of magnitude.

first period, the coefficients on top ownership are generally indistinguishable from zero. However, in the latter two periods, the coefficients are positive and statistically significant at the 1% level.[9]

Furthermore, we run our regressions in annual subsamples and plot the coefficients in standard deviation units for a one-standard deviation change in ownership by the top 10 institutions. We report this result in Figure 2. It is evident from the graph that coefficients increase over time. At the end of the sample, the effect of interest is nearly 16%, which is substantially larger than the average effect in the sample (3.3%). The increase in the effect of interest tracks the overall rise in the size of the largest institutional investors over time as reported in Figure 1. We conclude that the association between large institutions' ownership and volatility has grown along with the increase in their market share.

4.2 Identification: A Merger of Large Institutional Investors

While the association between large institutional investors and volatility is strong, it may not necessarily reflect a causal relation. For example, one possible explanation for this correlation is that large institutional investors might prefer holding popular stocks, which may be more volatile due to intense trading. In the next analysis, we exploit a natural experiment that can provide causal evidence.

We rely on the merger of Blackrock and BGI in December 2009. Our test compares the relation between institutional ownership and stock-level volatility before and after this merger. If the size of the institutional investors affects the volatility of the stocks in their portfolios, ownership by the merged institution should have an impact on the volatility of the stocks that before the merger were held by a non-top institution. The identifying assumption is that the merger is an exogenous event relative to the volatility of the stocks in the portfolios of the two original institutions.[10]

[9] Summary statistics for these subsamples are in the Internet Appendix, Table IA.1. In the Internet Appendix, we also report tests over different subsamples. We find that the effect of interest is present during the 2007–2009 financial crisis, other crisis periods, as well as outside of crisis periods (Table IA.5).

[10] Right before the merger, BGI held equities worth about $596 billion and was the largest institution as of the end of 2009, while BlackRock held equities worth about $156 billion and ranked in the 12th position. After their merger, in December 2009, the combined entity was the largest institutional investor in the equity market, overseeing approximately $815 billion in equities.

An important question relates to the exogeneity of the merger with respect to the outcome variable of interest, stock volatility. In fact, the motivation for the merger resided in Barclays' desire to sell some of its divisions to strengthen its balance sheet following the financial crisis. Hence, the reason for the merger appears to have been unrelated to the volatility of the underlying securities (see also Azar, Schmalz, and Tecu, 2017). The merger was announced on June 11, 2009 and was completed in December of 2009. Therefore, we expect the effect of the trading activity of the merged institution to start manifesting itself in stock prices from the first quarter of 2010.

BlackRock ranked number 12 before the merger and it became the top firm in the market following the merger. Hence, the stocks that were owned by BlackRock experienced a change of status following the merger. In particular, they ended up being owned by the largest institution in the market, while they were previously owned by an institution ranked below the top 10. We exploit this change of status as our natural experiment. The extent of treatment for each stock depends on the amount of ownership by BlackRock before the merger.

Our main specification resembles a difference-in-differences approach. Specifically, in our first set of tests, we define the treatment variable to be ownership by BlackRock in 2009/Q3, i.e., the last complete quarter before the merger. This quantity represents the amount by which a stock that was owned by a non-top institution (pre-merger BlackRock) ends up being owned by a top institution after the merger (post-merger BlackRock).

$$Volatility_{iq} = Treatment_i \times Post\ Merger_q + Controls_{i,q-1}$$

$$+Time\ FE_q + Stock\ FE_i + \varepsilon_{iq} \tag{6}$$

where the *Post Merger* dummy is an indicator for whether the quarter is 2010/Q1 or later. The main variable of interest is the interaction between *Treatment* and the *Post Merger* dummy. We control for the usual stock characteristics (main effects and interactions with the merger indicator) and for time and stock fixed effects. Standard errors are block-bootstrapped clustering by stock and quarter. The pre-merger window ranges between 2007/Q4 to the completion of the merger (2009/Q4). We look at various post-event windows, from one quarter to eight quarters after the merger, adding one quarter at a time to the estimation sample.

The results are reported in Table 4, Panel A. The samples in columns (1)-(8) include post-merger periods ranging from one to eight quarters, respectively. We find a strongly significant effect of treatment after the merger. Using the summary statistics in Table 1, when eight quarters after the merger are in the sample, a one-standard-deviation increase in the interaction variable is associated with a 1.6% increase in volatility in standard deviation units (0.009*4.270/2.340). The economic magnitude is not as large as for the full sample regressions of Table 2. However, this experiment focuses on a single firm and studies the incremental impact relative to the pre-merger BlackRock, which was already a sizeable asset manager (top 12). The strong statistical significance of the result reassures us on the causal interpretation of the estimates in Table 2, which is the main purpose of this exercise.

In Panel B of Table 4 reports results in which *Treatment* is instead a dummy for a high level of pre-merger ownership by Blackrock (i.e., stock ownership greater than the median ownership by Blackrock). In this case, the increase in volatility for treated stocks ranges between 13 bps and 25 bps. In units of standard deviation of the dependent variable, these slopes translate into an increase between 5.5% and 10.6%.

After a merger there is usually a period of portfolio adjustment. The combined entity may need to close some portfolios and possibly move the capital to other ones. These activities may mechanically lead to more coordinated trading and higher volatility for the portfolio stocks. To insulate from this potential effect, in Panel C of Table 4, we exclude the four quarters in the first year after the merger. The results remain significant and of similar magnitude.

To study whether the increase in volatility for treated stocks predates the merger, we generate plots of the quarterly regression coefficients of the treatment variable (in dummy variable form for the above-median ownership by Blackrock) and display them in Figure 3.[11] The figure shows the difference in volatility between the treated stocks and the matched controls. The merger effect is clear. In the pre-period, the difference in volatility between the two groups is not significantly different from zero. However, in the post-merger period, the treated stocks experience significantly higher volatility than the control group in most of the quarters under consideration.

[11] To construct this graph, we identify a control sample with similar pre-merger volatility to the treated stocks using propensity score matching (Abadie and Imbens, 2006).

What ultimately matters is the double difference between treatment and control groups before and after the merger, which is proven in the regression analysis of Table 4.

We perform additional robustness analysis for the tests in Table 4. First, in Internet Appendix Table IA.10, we remove the financial crisis from the pre-merger merger period, as it was a period of high volatility. In Panel A, we remove 2008/Q4 from the sample. In Panel B, we remove all quarters from 2008/Q3 through 2009/Q1. In both cases, the results remain significant. Second, in Internet Appendix Table IA.11, we run placebo tests choosing fictional dates for the merger, before the actual merger date. Specifically, we choose 2008/Q4, in Panel A, and 2007/Q4 in Panel B. Consistent with the effect that we estimate in Table 4 being related to the merger, we do not find any significance around these alternative dates. Finally, in Internet Appendix Table IA.12, we replace the treatment variable, i.e. pre-merger ownership by BlackRock, with an alternative treatment, i.e. pre-merger ownership by BGI. Consistent with the fact that firms with large BGI ownership were already exposed to the large firm ownership before the merger, we find no effect of this new treatment variable after the merger.

Overall, the exogenous nature of the merger event with respect to the volatility of the portfolio securities as well as the significance and robustness of the findings in Table 4 corroborate a causal interpretation of the positive relation between volatility and ownership by large institutions.

4.3 Noise in Prices

The analysis in Section 2 posits that large institutions increase volatility because of the larger price impact of their trades. Price impact is a temporary movement in prices that is subsequently reversed, i.e it is noise. In what follows, we explore this conjecture by studying the effect of large institutional ownership on return autocorrelation.

We test this relation both for the entire sample and for the Blackrock-BGI merger. Our tests follow the specification in Equations (5) and (6), replacing volatility with a measure of return autocorrelation. Specifically, we use returns adjusted following Daniel, Grinblatt, Titman, and Wermers (1997, DGTW) to filter out return variation originating from the size, book-to-market, and momentum stock characteristics and calculate the autocorrelation of daily adjusted returns within a quarter.

In Table 5, Panel A, we report estimates from the regression of the absolute value of stock-return autocorrelation on *Top institutional ownership* and controls, including stock and quarter fixed effects. Standard errors are double-clustered at the stock and quarter level. The estimates suggest a significantly positive relation between the absolute value of return autocorrelation and large firm ownership (up to the top 10^{th} institution).[12]

Panel B of Table 4 casts the analysis in the framework of the natural experiment, i.e. the Blackrock-BGI merger. We find that the absolute value of autocorrelation increases. Given the exogenous nature of the merger, this result supports a causal interpretation of the association between top institutional ownership and return autocorrelation. Moreover, in Panel C of Table 4, we find that the signed autocorrelation decreases after the merger. That is, the autocorrelation of returns become more negative because large institutional ownership, consistent with the view that large institutions impound temporary shocks into prices that subsequently revert.

In sum, this evidence corroborates the view that large institutions' trades are more conducive to temporary price pressure than trades by smaller institutions. In other words, ownership by large institutions seems to increase noise in stock prices.

4.5 Price Fragility

In periods of turmoil, portfolio liquidations become more likely and the trades of large institutional investors may be more impactful than in normal times because they take place in an already illiquid market. Therefore, top institutions' trades may induce significant price dislocations at these times.

To test this possibility, we identify periods of market stress by focusing on the return of the overall market. We identify bad times as quarters in which the realization of the excess market

[12] Using the statistics in Table 1, a one-standard deviation change in ownership by the top 10 institutions is associated with a 1.6% of a standard deviation increase in the dependent variable.

return is in the bottom 5% of the quarterly return distribution. We test whether stocks with higher ownership by top institutions earn significantly lower returns in these quarters.

Because stock characteristics, beyond ownership by top institutions, can be a driver of returns at times of market stress, we focus on DGTW-adjusted returns. We further control for these effects through regression controls (size, book-to-market, and past returns). Additionally, we control for liquidity-related effects by including measures of stock-level liquidity in the regression (the Amihud ratio and inverse stock price). These controls absorb the known asset pricing and microstructure effects that are unrelated to large institutions' ownership.

Table 6 shows the results of this analysis. We find that the relation between ownership by large institutions and the level of returns is significantly negative in times of extreme market conditions. Interestingly, the relation is not significantly different from zero in normal times. This effect is not present for lower-ranked institutions. Hence, we view this result as evidence that orderly liquidations become harder for a large institution in times of market turmoil, given the sheer size of the blocks that are brought to the market during these low liquidity episodes. The economic magnitude is also important. For example, based on column (4) and the summary statistics in Table 1, in a bad quarter, a one-standard deviation increase in ownership by the top 10 institutions is associated with lower quarterly returns by 9.17% of a standard deviation (–0.191*0.073/0.148).

The quarterly frequency at which we compute returns justifies the claim that the effect of large institutions is not merely microstructure noise that washes out at lower frequency. Rather, it persists at frequencies that are relevant for long-term investors. Consistent with the evidence in Coval and Stafford (2007), we interpret this finding as the result of the persistence of portfolio flows, which ultimately induces persistence of trades and price impact.[13]

The finding of a negative correlation between large institutional ownership and stock returns during times of market stress is consistent with the view that large institutions, when engaging in

[13] Further supporting evidence of the persistence of the effect of large institutional ownership on prices at lower frequency comes from Internet Appendix Table IA.3, in which we use weekly, monthly, and quarterly measures of price volatility as dependent variables.

liquidations, impose a high liquidity demand on the market. This evidence corroborates the regulators' concern that large institutions may be destabilizing at times of turmoil.[14]

5 Studying the Channel: Evidence on the Granularity of Large Institutional Investors

Centralized functions, such as research, marketing, and risk management, may create correlated behavior across the units within a large firm, which in turn generates correlated trades coming from the different divisions within the organization. These trades are likely to have a significant price impact because they do not offset one another, but rather they hit the market in the same direction. Price impact and volatility result from the price concessions that liquidity providers require to accommodate the large trades. These effects are mitigated for independent investors, because their trading behavior is less correlated. Hence, the price impact of the trades of independent investors would be less pronounced.

In this section, we empirically test whether different units within the same institution display more correlated behavior than entities that are part of independent organizations.

5.1 Correlated Flows

Capital flows across units within large institutions may be correlated for several reasons. Marketing efforts aimed at creating a family brand and at cross-selling an array of family products are likely to increase the correlation of flows to the units within the organization. For example, when a provider of a 401(k)-pension plan includes multiple funds from a given family among the investment options, correlated flows will hit all of the funds in the family. Moreover, mutual funds often inherit the reputation of the umbrella organization and are identified with it, as in "a Fidelity fund." Hence, the stellar performance of a given fund may induce investors to invest in other family funds as well (as in Nanda, Wang, and Zheng, 2004). Or, investors may perceive funds in the same family as following a similar investment style and move capital in and out of the family as a result

[14] In the Internet Appendix, we also study the relationship between skewness and large institutions' ownership. In Table IA.3, Panel B, we find that stocks that are held by large institutions display significantly lower skewness, which is computed non-parametrically as in Ghysels, Plazzi, and Valkanov (2016). This finding is consistent with Table 6 and supports the conclusion that large institutional investors can be destabilizing for prices.

of style investing (Barberis and Shleifer, 2003). Also important, events that occur at the level of the parent company may trickle down to affect the entities within it. As an example, Bill Gross's departure from PIMCO triggered outflows from funds at PIMCO that Gross, at the time CIO of the firm, was not directly managing. Because of these outflows, five of PIMCO's funds appeared in the infamous ranking of the 10 funds with the heaviest customer redemptions in 2014.

The discussion suggests that the correlation of investor flows across units of a unique institution is higher than across independent institutions. Testing this conjecture is not feasible using the quarterly 13F data, because these data do not include investor flows, but only changes in long equity positions. To overcome this empirical hurdle, we use mutual fund data. We then test whether the pairwise correlation of flows between funds in the same family (i.e., same management company) is higher than the correlation between funds in distinct families.[15]

We regress the correlation coefficient on an indicator variable for whether the pair belongs to the same family. Panel A of Table 7 presents the results. Columns (1)-(4) use the entire universe of mutual funds but restrict the sample to a 1% randomly chosen subsample of the data (for computational efficiency). Columns (5)-(8) report results restricted to funds managed by the 20 largest institutions in the same sample. The different columns correspond to different combinations of fixed effects: from a specification with time fixed effects (columns (1) and (5)) to a specification that includes fixed effects for each fund *i*-year and fund *j*-year (columns (4) and (8)). The standard errors in these regressions are clustered along three dimensions: year, fund *i*, and fund *j*. Despite the different levels of fixed effects, the results are very similar across specifications. Using the coefficient in column (1), we find the correlation coefficient is about 3.2% higher when funds are within the same family; that is, it is about twice as large as the sample average correlation. Given that the standard deviation of the dependent variable is approximately 33.2% (Table 1, Panel A), funds that belong to the same family have a correlation that is about 10% of a standard deviation

[15] The CRSP Mutual Fund Database does not have an explicit mutual fund family identifier, so we create one manually. We then compute the monthly flows for each share class using the monthly assets and net return figures in CRSP, and then aggregate the flows at the portfolio level. The flow-correlation measure is constructed using 12-month rolling Pearson correlations of the monthly percentage of portfolio flows. To this end, we generate a dataset that includes all combinations of mutual fund pairs. We restrict our sample to only those correlations that have non-missing flows in the last 12 months. Finally, to avoid overlapping observations, we keep one observation per fund pair-year as of December. We end up with a sample of 249,665,892 observations on 8,410 different mutual funds belonging to 924 family groups in the period between 1980 and 2016. Table 1, Panel A, shows the summary statistics for the variables used in this analysis.

higher than that of the entire population of funds. Hence, the effect is economically significant. We find that the result is robust for funds managed by the top institutions. For this subsample, we find the correlation coefficient is about 2.4% higher when funds are within the same family.

5.2 Correlated Trades

Next, we explore whether trades are more similar across units within an organization than across independent firms. Again, we focus on mutual fund families in order to identify portfolio holdings of sub entities. We posit that mutual funds that are part of a family have access to common resources when making investment decisions. For example, mutual fund managers in the same firm may rely on the same equity research done by a centralized research department, they may share information with neighboring managers in the spirit of Hong, Kubik, and Stein (2005), and may be bound by the same risk management rules set by the risk management department of the organization. Also relevant, a recent paper by Auh and Bai (2018) shows that there is information sharing between equity and bond mutual funds in the same fund family.

We measure trades at the quarterly frequency using changes in holdings.[16] Given the evidence on flow correlation that we have just produced, it is natural that same-family funds would adjust their portfolios in the same direction when they receive flows. Hence, to obtain a result that is not mechanically related to our prior evidence, we focus on mutual funds' *active trades*. An active trade is the residual change in a stock quarterly holding after subtracting the change in holding that would result from a simple rescaling of the portfolio proportional to the quarterly flows (Greenwood and Thesmar, 2011).

We regress fund-quarter level pairwise correlations in active trades for any two funds in our database on the same-family dummy. The results of the analysis are presented in Table 7, Panel B. Columns (1)-(4) correspond to funds managed by all institutions, and columns (5)-(8) correspond to funds managed by the largest 20 institutions. The standard errors in these regressions are clustered along three dimensions: year, fund i, and fund j. The estimates indicate that mutual

[16] We infer mutual fund portfolio composition from Thomson-Reuters Mutual Fund database and the CRSP Mutual Fund Database. We rely on Thomson-Reuters mutual fund database for historical holdings of mutual fund portfolios between 1980 and 2012, and rely on CRSP mutual fund database for the portfolio holdings after 2013 due to Thomson-Reuters data quality issues that also affected their mutual fund ownership database in recent years.

funds that belong to the same family have higher correlation between trades. The correlation is about 2.5% higher for same-family funds in the most restrictive specification for all funds, and 2.2% higher for funds managed by the largest institutions. Again, the effect is highly economically significant (36% and 32% of a standard deviation for all and large institutions, respectively), given that the standard deviation of the dependent variable is about 6.9%.[17]

5.3 Identification using the Merger Natural Experiment

Next, we confirm the conclusions on flow and trade correlation in the context of the natural experiment of the BlackRock-BGI merger. This analysis helps to provide a causal interpretation of the results in Table 7. Furthermore, it sheds light on the channel driving the effect of the merger on stock volatility that we found in Table 4.

As far as flows are concerned, we compute the annual pairwise correlation among equity mutual funds using monthly returns within a year. We consider a four-year window centered on the merger (2008-2011). The post-merger period contains the two years after the completion of the merger (i.e. December 2009). We include in our tests the universe of all funds as in Table 7. The treated funds are those that belong to separate pre-merger companies (either BlackRock or BGI) and end up in the same company after the merger. We also include controls for pairs of funds that were already in the same company (either BlackRock or BGI) before the merger. We use different combinations of fixed effects and the standard errors are bootstrapped.

Panel A of Table 8 shows that the coefficient on the *Treatment×Post-Merger* Dummy is positive and significant. Following the merger, funds that were part of separate companies experience an increase in flow correlation by an average of 4.3% relative to funds that belonged to the same company before the merger. This effect is economically important, as the standard deviation of the correlation of flows in the sample is about 32%.

We note that in Panel A of Table 8, the interaction term $BlackRock\_or\_BGI\_Pair \times Post$ is statistically and economically significant. While not related to the main effect that is being

[17] In the Internet Appendix, we show that mutual within the same family also display significantly higher correlation in holdings (Table IA.14, Panel A) and higher correlation in returns (Table IA.14, Panel B).

studied here, this result is consistent with our priors. In particular, it can be explained based on the growth of passive investment. Right before the merger, BGI funds were mostly passive (about 98% by AUM), whereas BlackRock funds were mostly active (about 99% by AUM).[18] In the Internet Appendix Table IA.9, we re-run the analysis of Table 8, Panel A, splitting the variable BlackRock/BGI Pair into BlackRock Pair and BGI Pair. We show that the interaction with the post-period is only significant for the BGI Pair. Hence, the passive funds from BGI drive the significance of the interaction term. At the time of the merger, the asset management industry was experiencing the start of the boom in passive investing. The iShares ETFs by BGI were at the forefront of this trend. In particular, Internet Appendix Figure IA.1 shows that the bulk of the flows into BlackRock's equity funds originated from the passive funds inherited from BGI. Therefore, given the trend in passive investing at the time of the merger, it is not surprising that the passive funds in the post-merger BlackRock experienced an increase in flow correlation. These funds were all regarded as attractive passive vehicles by investors and experienced similar flows.[19]

Next, we study correlation in trading activity.[20] To this purpose, we proxy trades with the quarterly change in fund holdings. We compute this correlation for each pair of funds in the quarter as the correlation of the stock-level changes in portfolio weights. We retain the fourth quarter observations to keep the size of the sample manageable. Panel B of Table 8 replicates the specifications of Panel A using the correlation of holdings changes as dependent variable. We find that the coefficient on the *Treatment×Post-Merger* Dummy is positive and significant in our most

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[18] Based on CRSP mutual fund data, BGI funds that were acquired by BlackRock were mostly index funds/ETFs with the exception of money market funds. For these acquired funds, total assets were $368,785 million, of which Index Fund Assets were $362,329 million, and ETF Assets were $358,169.6 million, as of Q4 2009 (the quarter of the merger). We identified 706 share classes (180 portfolios) of Blackrock funds in the pre-merger period. For the 663 share classes (178 portfolios) of Blackrock funds that were active and part of Blackrock in September 2009 (last quarter prior to the merger effective date), total assets were $305,945 million and Index Fund Assets $3,362 million.

[19] We note further that this development does not detract from the validity of the main claim of the paper. In fact, our focus is on the flow correlation between BlackRock (mostly active) and BGI (mostly passive) funds. As evident in Internet Appendix Figure IA.1, the Active Equity Funds in the post-merger BlackRock also experienced *positive* flows. This fact is in sharp contrast with the development in the overall asset management sector (Internet Appendix Figure IA.2), where active funds experienced a sharp decline in AUM. Hence, the increase in active flows towards BlackRock's active funds seems to be a distinct phenomenon that can be reasonably imputed to the visibility that this company received after the merger with BGI. This development is behind the post-merger increase in correlation between BGI and BlackRock funds that is the focus of Table 8.

[20] We can identify 706 share classes for around 180 different funds for Blackrock before the merger. For BGI, before the merger, we identify 288 share classes for 248 different funds. Among the BGI funds, after the merger, we identify 219 surviving share classes corresponding to 198 funds. Out of these 198 surviving funds, 194 have non-missing index fund flag in CRSP, i.e. they are classified as pure index or enhanced index funds.

stringent specification. Following the merger, funds that were part of separate companies experience an increase in trade correlation by an average of 0.4% relative to funds that belonged to the same company before the merger. Because the standard deviation of trade correlation in the sample is 16.8%, the economic magnitude is about 2.3% of a standard deviation.

5.4 Large Institutions vs. Synthetic Institutions

The evidence that large institutional investors behave in a more correlated way than independent firms suggests two additional conjectures on the granular nature of large institutions. First, the trades of large institutions should be more concentrated, i.e., restricted to a smaller set of stocks. This happens, for example, if the different managers within a given firm rely on the same research sources. Second, we expect that large institutions place trades that are larger in absolute value than the trades placed by a collection of independent institutions that manage the same amount of total assets. This prediction emerges because correlated capital flows and correlated trading behavior prevent diversification of trades, so that trades reach the market as a large shock. On the other hand, uncorrelated trades from independent institutions are more likely to be netted against each other.

To test these conjectures, we compare large institutions' trades to the trades of smaller institutions that add up to the same total equity holdings as the large institution. The comparison, therefore, aims at keeping the size of the assets under management constant so that we can analyze the effect of variation in the organizational structure. In this analysis, we proxy for trades using the quarterly changes in 13F holdings at the stock level. For each large institution among the top 10 in a given quarter (called here the "original institution"), we generate a sample of 99 "synthetic institutions" in a block bootstrapping procedure. Each synthetic institution results from pooling together institutions that rank below the 10th largest institution. These component institutions are randomly drawn without replacement until the dollar value of the equity holdings of the original institution is matched.[21] For the synthetic institutions to represent a valid benchmark, we assume

[21] We add a fraction of the last institution drawn to ensure we exactly match the total dollar value of the equity holdings of the random sample to those of the large institution. In 1980, the size of the equity portfolio of the largest institutional investor equaled the aggregate size of about 25 random institutions. In contrast, reflecting the dramatic increase in

that the type of investors or investor behavior in the synthetic institutions is comparable to what would prevail in the counterfactual market configuration in which no large institutions were present.

5.4.1 Portfolio Holdings

We first examine the size of the universe of stocks that large institutional investors hold. In Table 9, Panel A, we compute the average number of stocks that make up certain fractions of the institutional portfolio. For example, 50% of the equity portfolio of the top institutional investor in the economy consists of 79 stocks on average (the largest holdings). In contrast, the average number of stocks that account for 50% of the portfolio of a similar-size synthetic portfolio is 93. The same pattern appears in almost every cell in the panel: The number of stocks held by the original institutional investors is significantly lower (in the order of 24% to 39% lower) than the number of stocks held in the portfolio of the synthetic institutions. Interestingly, on average the portfolios of the top 10 original institutions contain 1,995 stocks, while 2,550 stocks comprise the portfolio of the synthetic institutions.

These findings imply that the original large institutional investors allocate a given amount of money to a smaller set of stocks than the synthetic institutions. In turn, this fact suggests that top institutions are likely to trade each stock in larger amounts and to have bigger price impacts. The next analysis, therefore, focuses on trade size.

5.4.2 Trade Size

Given the prior findings of correlated flows and similar and concentrated portfolio holdings, we anticipate that the sub-entities within large institutions are less likely to execute offsetting trades. Hence, we predict that large institutions will execute larger trades in comparison to their synthetic counterparts.

To test this supposition, we study the distributions of trade size (i.e., absolute changes in portfolio holdings) for the original large institutional investors and the synthetic ones. We construct a stock-quarter indicator for whether the original institution's trade is above a given

concentration in the industry, in 2016, 424 random institutional investors were needed to match the size of the top firm.

percentile of the distribution of the synthetic institutions' trades. Then, we average this indicator across stocks and quarters. For each top-10 institutional investor, Panel B of Table 9 reports the average across stocks and quarters of this indicator for the 50th, 90th, 95th, and 99th percentiles. On average across the top-10 institutions, 56.1% of trades by the original institution are larger than the trades placed by 50% of the synthetic institutions. Moreover, 16.2% of the trades are larger than 90% of the synthetic institutions' trades, 9.4% of trades are larger than the 95th percentile, and 3.7% of trades are larger than the 99th percentile. These numbers exceed the percentages expected if the distributions of trade size were the same for the original and synthetic institutions (i.e., we would expect 50% of trades to be above the 50th percentile, 10% to be above the 90th percentile, and 1% to be above the 99th percentile).

In sum, the evidence shows that the quarterly changes in equity portfolio holdings for large institutional investors are significantly larger than for the synthetic institutions. Hence, large institutions impose a higher liquidity demand on the market than smaller independent firms. This liquidity demand can translate into price impact if the investors taking the other side of these trades require price concessions. In turn, the price impact of these trades can explain the effect of large institutions on volatility, noise, and price fragility that we document in the first part of the paper.

6 Conclusion

Motivated by the dramatic increase in the concentration of institutional ownership in the stock market, we investigate the effect of large institutional investors on stock prices.

We find that ownership by large institutions correlates with stock price volatility, autocorrelation in returns (a measure of price inefficiency), and the magnitude of price drops at times of market stress (a measure of price fragility). Using a natural experiment, i.e. the merger of two large institutional investors, we develop a causal interpretation of the effect of large institutions on asset prices.

The paper also studies the channel for this effect. We find that funds within the same family exhibit higher flow correlation and higher correlation of trades than funds belonging to independent families. The merger-based natural experiment suggests that this evidence is the causal effect of membership in the same family. Furthermore, large institutions trade in a restricted universe of stocks relative to a collection of firms of the same total size, and their trades are bigger in absolute value. This evidence suggests that large institutions are granular. That is, the sub-entities within the same firm display correlated behavior. Hence, when these asset managers are hit by idiosyncratic shocks, diversification is not as strong as if the shocks hit managers in independent families. As a result, the trades of large institutions are more impactful for prices than the diversified trades of a collection of small institutions.

Our results have implications in terms of regulatory design. In particular, they inform the debate about the optimal size of an asset management firm. Regulators have been questioning the systemic implications of large asset managers. We show that combining different institutions within a unique conglomerate affects the “production function” of all the entities that are involved. The access to capital as well as the investment and trading activities of the different components within a conglomerate display higher correlation than it is the case for independent firms. This correlated behavior, combined with the sheer size of the conglomerates, has repercussions on asset price stability that is mostly felt at times of market stress. Especially the last consideration supports the regulatory concerns and suggests that excessive concentration in the asset management industry may be harmful from the point of view of systemic risk. Of course, any regulatory action should weigh the decrease in price efficiency and the increased potential of large price drops against the economies scale in information production and trading that large institutions can achieve and can pass on to their clients. The ultimate impact on welfare of large institutional investors remains an open question for future research.

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Figure 1. Time Series of Large Institutions' Ownership

The chart shows the aggregate equity holdings by all institutions and the top institutions over time, as a percentage of total market capitalization of the U.S. equity market.

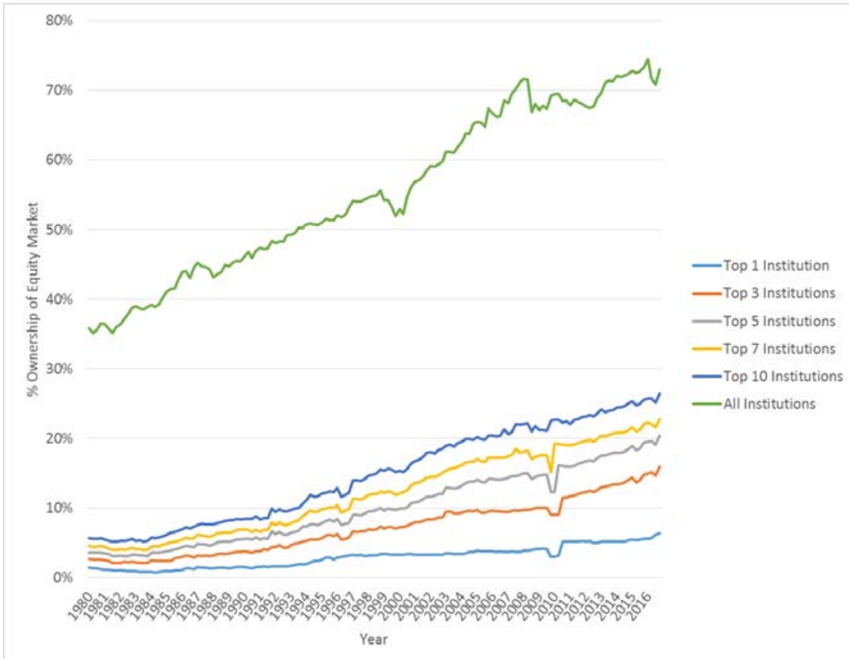

Figure 2. Yearly Coefficients

This figure presents slope coefficients and moving averages of slope coefficients from Ordinary Least Squares (OLS) regressions as in Equation 1, run by year. The dependent variable is the stock's *Daily volatility*, which is computed from daily returns during quarter q. The slopes are expressed in standard deviation units of the dependent variable for a one standard deviation change in top 10 institutions' ownership. The key independent variable, which is presented below, is the coefficient on *Top inst. ownership*. The sample period is 1980/Q1–2016/Q4.

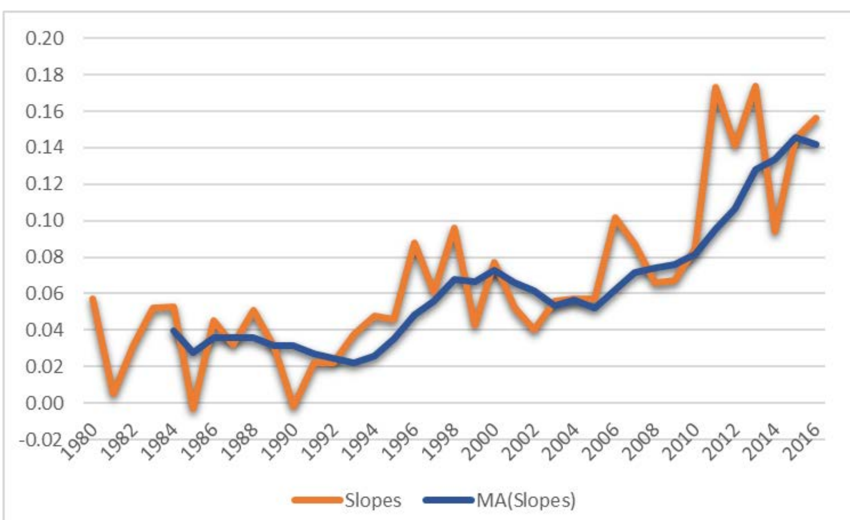

Figure 3. Treatment Effect on Volatility around the Merger

This figure presents slope coefficients from differences-in-differences regressions. We use the event of the merger between BlackRock and BGI in December 2009 to test the relation between volatility and ownership by large institutions. Point 0 on the x-axis represents the quarter of the merger, 2009/Q4. The dependent variable is the stock's *Daily idiosyncratic volatility*, which is computed from daily returns during the next quarter. The key independent variable, which is represented below, with 95% confidence standard error bands, is the interaction between a dummy variable that equals one if the firm is in the top 50% of pre-merger ownership by Blackrock and a quarter dummy. The control sample is selected using propensity score matching based on a probit model for the probability of treatment as a function of the average volatility during the pre-period. The chosen algorithm implements k-nearest neighbors Mahalanobis matching, with k=4.

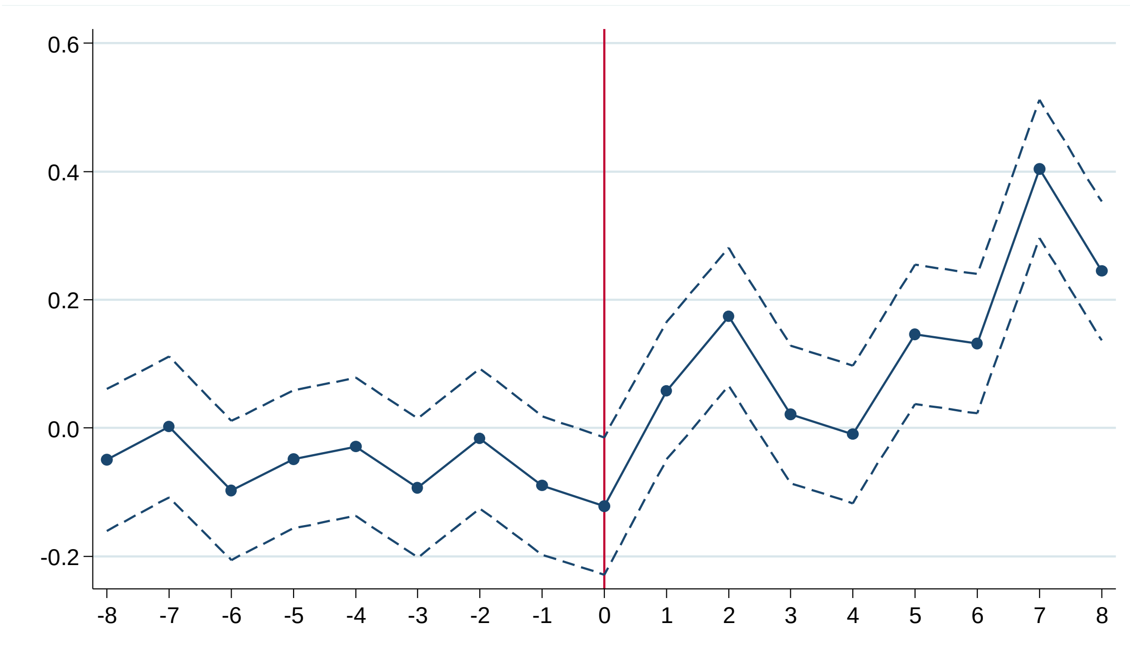

Table 1. Summary Statistics

This table presents summary statistics for key variables used in the analysis. Panel A presents statistics for variables that are used in different parts of our analysis. Panel B presents correlations of key variables used in the analysis. Panel C focuses on extreme months and reports stock-month level statistics. Unless otherwise specified, the sample period is 1980/Q1–2016/Q4.

	N	Mean	Std Dev	Min	p25	Median	p75	Max
Stock-quarter-level sample								
Daily volatility (%)	666,605	3.510	2.550	0.210	1.834	2.785	4.331	25.691
Top 3 insts ownership (q-1)	666,605	0.042	0.051	0.000	0.002	0.022	0.059	0.339
Top 5 insts ownership (q-1)	666,605	0.056	0.068	0.000	0.005	0.029	0.082	0.517
Top 7 insts ownership (q-1)	666,605	0.067	0.078	0.000	0.008	0.036	0.100	0.610
Top 10 insts ownership (q-1)	666,605	0.081	0.090	0.000	0.011	0.046	0.122	0.709
Top 11-Top 20 ownership (q-1)	666,605	0.033	0.045	-0.165	0.001	0.012	0.051	0.537
Top 21-Top 30 ownership (q-1)	666,605	0.022	0.033	0.000	0.000	0.006	0.032	0.636
Top 30-Top 50 ownership (q-1)	666,605	0.027	0.039	0.000	0.000	0.009	0.042	0.737
Ownership by "middle" institutions (q-1)	666,605	0.282	0.228	0.000	0.074	0.240	0.461	1.000
Ownership by all institutions (q-1)	666,605	0.380	0.301	0.000	0.110	0.320	0.616	1.273
Ownership by bottom institutions (q-1)	666,605	0.017	0.033	0.000	0.000	0.005	0.018	0.311
1 / price (q-1)	666,605	0.246	0.613	0.005	0.038	0.076	0.196	10.548
Amihud illiquidity (q-1)	666,605	0.360	0.588	0.000	0.006	0.074	0.473	4.488
log(market cap) (q-1)	666,605	5.221	2.086	0.408	3.660	5.059	6.644	11.582
Past 6-month return (q-3 to q-1)	666,605	0.065	0.423	-0.942	-0.161	0.027	0.221	8.536
Book-to-market (q-1)	666,605	0.750	0.658	-0.062	0.334	0.595	0.961	10.142
Greenwood and Thesmar Fragility	498,482	0.118	0.195	0.000	0.014	0.047	0.122	1.540
Idiosyncratic Volatility	657,736	3.210	2.500	0.281	1.580	2.470	3.970	25.700
Systematic Volatilty	657,736	1.300	1.010	0.014	0.651	1.030	1.620	16.100
Daily Autocorrelation	591,089	-0.086	0.187	-0.623	-0.210	-0.076	0.045	0.457
Abs(Daily Autocorrelation)	591,089	0.163	0.127	0.000	0.062	0.133	0.236	0.623
Return Regressions Sample								
DGTW Returns	479,839	-0.003	0.135	-0.340	-0.086	0.000	0.077	0.357
Top 10 insts ownership (q-1)	479,839	0.072	0.073	0.000	0.014	0.049	0.110	0.484
During worst quarters (bottom 5% of mkt return):								
DGTW Returns	18,758	0.022	0.148	-0.340	-0.070	0.012	0.124	0.357
Top 10 insts ownership (q-1)	18,758	0.078	0.073	0.000	0.017	0.057	0.123	0.396
Merger Experiment Sample (2007/Q4-2009/Q4)								
Daily volatility (%)	61,876	3.790	2.340	0.208	2.240	3.200	4.630	21.800
Continuous Treatment × Post	61,876	0.003	0.009	0.000	0.000	0.000	0.002	0.124
Continuous Treatment	61,876	0.007	0.013	0.000	0.000	0.003	0.007	0.124
Treatment × Post	61,876	0.250	0.433	0.000	0.000	0.000	1.000	1.000
Treatment	61,876	0.539	0.499	0.000	0.000	1.000	1.000	1.000
Daily Autocorrelation	57,189	-0.073	0.163	-0.534	-0.181	-0.066	0.041	0.335
Abs(Daily Autocorrelation)	57,189	0.142	0.109	0.000	0.055	0.118	0.205	0.534
Mutual Fund Sample								
Pairwise Flow correlation	249,665,892	0.030	0.332	-1.000	-0.192	0.028	0.253	1.000
Pairwise Return correlation	249,665,892	0.566	0.418	-1.000	0.352	0.729	0.888	1.000
Same management company indicator	249,665,892	0.008	0.088	0.000	0.000	0.000	0.000	1.000
Pairwise Correlation of Active Share Weights	115,398,353	-0.257	0.225	-1.000	-0.415	-0.239	-0.084	1.000
Pairwise Correlation of Active Rebalancing Trades	126,533,009	0.009	0.069	-1.000	-0.001	0.000	0.003	1.000

Table 2. Ownership by Large Institutional Investors and Stock Volatility

This table presents ordinary least squares regression results. The dependent variable in both panels is the stock's *Daily volatility*, which is computed from daily returns during the next quarter, quarter q. All independent variables are measured during quarter q-1. The key independent variable is the *Top inst. ownership* of the largest institutional investors in a given stock. Panel B replicates the analysis from Panel A, but includes Greenwood and Thesmar's (2011) fragility measure. Time and stock fixed effects are also included. The sample period is 1980/Q1–2016/Q4. Appendix A provides variable descriptions. *t*-statistics based on standard errors clustered at the stock and quarter level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Ownership by Large Institutional Investors and Daily Volatility

Dependent variable:	Daily volatility (q) (%)						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	1.096***	1.080***	1.071***	0.945***	1.146***	0.674***	0.238
	(4.637)	(5.542)	(6.401)	(6.625)	(6.493)	(4.087)	(1.576)
Ownership by "middle" institutions (q-1)	0.152***	0.122**	0.093*	0.082	0.009	0.086	0.115*
	(2.686)	(2.093)	(1.679)	(1.434)	(0.150)	(1.466)	(1.872)
1 / price (q-1)	0.599***	0.599***	0.598***	0.598***	0.599***	0.600***	0.600***
	(9.845)	(9.840)	(9.831)	(9.838)	(9.867)	(9.874)	(9.876)
Amihud illiquidity (q-1)	1.479***	1.477***	1.476***	1.476***	1.478***	1.481***	1.481***
	(23.635)	(23.562)	(23.548)	(23.533)	(23.571)	(23.622)	(23.638)
log(market cap) (q-1)	-0.293***	-0.297***	-0.298***	-0.299***	-0.282***	-0.278***	-0.277***
	(-11.164)	(-11.237)	(-11.259)	(-11.440)	(-11.446)	(-11.219)	(-11.212)
Past 6-month return (q-3 to q-1)	-0.109	-0.108	-0.107	-0.106	-0.111	-0.114	-0.114
	(-0.966)	(-0.956)	(-0.948)	(-0.941)	(-0.979)	(-1.005)	(-1.007)
Book-to-market (q-1)	0.013	0.012	0.012	0.013	0.016	0.015	0.015
	(0.480)	(0.455)	(0.466)	(0.478)	(0.589)	(0.560)	(0.577)
Ownership by bottom institutions (q-1)	-1.365***	-1.332***	-1.324***	-1.322***	-1.407***	-1.450***	-1.450***
	(-6.586)	(-6.496)	(-6.418)	(-6.451)	(-6.975)	(-7.117)	(-7.116)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	666,605	666,605	666,605	666,605	666,605	666,605	666,605
Adj R^2	0.666	0.666	0.666	0.666	0.666	0.666	0.666

Table 2. Ownership by Large Institutional Investors and Stock Volatility (Cont.)

Panel B: Including Greenwood and Thesmar's (2011) Fragility Measure

Dependent variable:	Daily volatility (q) (%)						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	1.066***	1.011***	1.074***	0.959***	1.130***	0.629***	0.479***
	(3.813)	(4.223)	(5.427)	(5.625)	(5.299)	(2.887)	(2.802)
Ownership by "middle" institutions (q-1)	0.166**	0.146**	0.110	0.094	0.029	0.005	-0.045
	(2.384)	(2.033)	(1.606)	(1.365)	(0.381)	(0.073)	(-0.551)
1 / price (q-1)	0.585***	0.585***	0.584***	0.584***	0.585***	0.586***	0.586***
	(9.578)	(9.577)	(9.569)	(9.575)	(9.589)	(9.603)	(9.608)
Amihud illiquidity (q-1)	1.492***	1.491***	1.490***	1.490***	1.490***	1.493***	1.493***
	(23.019)	(22.987)	(22.971)	(22.964)	(22.966)	(22.994)	(23.028)
log(market cap) (q-1)	-0.349***	-0.350***	-0.352***	-0.352***	-0.338***	-0.329***	-0.327***
	(-11.130)	(-11.148)	(-11.186)	(-11.288)	(-11.331)	(-11.169)	(-11.244)
Past 6-month return (q-3 to q-1)	-0.103	-0.103	-0.102	-0.101	-0.105	-0.109	-0.110
	(-0.936)	(-0.929)	(-0.921)	(-0.915)	(-0.953)	(-0.987)	(-0.988)
Book-to-market (q-1)	-0.021	-0.021	-0.021	-0.021	-0.018	-0.018	-0.017
	(-0.771)	(-0.782)	(-0.781)	(-0.771)	(-0.663)	(-0.653)	(-0.641)
Ownership by bottom institutions (q-1)	-1.373***	-1.353***	-1.344***	-1.342***	-1.399***	-1.428***	-1.427***
	(-5.771)	(-5.721)	(-5.677)	(-5.678)	(-5.976)	(-6.040)	(-6.063)
Greenwood and Thesmar Fragility (q-1)	0.178***	0.177***	0.173***	0.175***	0.218***	0.228***	0.240***
	(5.307)	(5.289)	(5.186)	(5.239)	(6.118)	(6.282)	(6.497)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	498,482	498,482	498,482	498,482	498,482	498,482	498,482
Adj R^2	0.665	0.665	0.665	0.665	0.665	0.664	0.664

Table 3. Ownership by Large Institutional Investors and Stock Volatility – Subperiod Analysis

This table presents ordinary least squares regression results. The dependent variable is the stock's *Daily volatility*, which is computed from daily returns during quarter q. The key independent variable is the *Top inst. ownership* of the largest institutional investors in a given stock. All independent variables are measured during quarter q-1. In Panel A, the sample period is 1980-1990; in Panel B the sample period is 1991-2003; and in Panel C the sample period is 2004-2016. Time and stock fixed effects are also included. Appendix A provides variable descriptions. *t*-statistics based on standard errors clustered at the stock and quarter level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: 1980-1990

Dependent variable:	Daily volatility (q) (%)						
Subperiod	1980-1990						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	0.719	0.237	0.479*	0.125	-0.206	0.127	0.192
	(1.464)	(0.719)	(1.683)	(0.562)	(-0.879)	(0.552)	(0.926)
Ownership by "middle" institutions	0.067	0.085	0.057	0.092	0.127	0.094	0.086
	(0.664)	(0.841)	(0.561)	(0.865)	(1.147)	(0.883)	(0.792)
1 / price (q-1)	0.222***	0.222***	0.222***	0.222***	0.221***	0.221***	0.221***
	(5.922)	(5.918)	(5.919)	(5.909)	(5.894)	(5.899)	(5.898)
Amihud illiquidity (q-1)	1.579***	1.578***	1.579***	1.578***	1.578***	1.578***	1.578***
	(14.926)	(14.956)	(14.961)	(14.966)	(14.967)	(14.963)	(14.967)
log(market cap) (q-1)	-0.472***	-0.472***	-0.472***	-0.471***	-0.471***	-0.471***	-0.471***
	(-10.180)	(-10.185)	(-10.201)	(-10.215)	(-10.206)	(-10.200)	(-10.204)
Past 6-month return (q-3 to q-1)	-0.197***	-0.197***	-0.197***	-0.197***	-0.198***	-0.198***	-0.198***
	(-4.483)	(-4.487)	(-4.472)	(-4.481)	(-4.498)	(-4.499)	(-4.493)
Book-to-market (q-1)	-0.175***	-0.174***	-0.174***	-0.174***	-0.174***	-0.174***	-0.174***
	(-4.188)	(-4.173)	(-4.173)	(-4.166)	(-4.168)	(-4.169)	(-4.167)
Ownership by bottom institutions (q-1)	-1.634***	-1.631***	-1.632***	-1.628***	-1.632***	-1.625***	-1.625***
	(-3.337)	(-3.328)	(-3.329)	(-3.322)	(-3.335)	(-3.314)	(-3.319)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	157,063	157,063	157,063	157,063	157,063	157,063	157,063
Adj R^2	0.682	0.682	0.682	0.682	0.682	0.682	0.682

Table 3. Ownership by Large Institutional Investors and Stock Volatility – Subperiod Analysis (Cont.)

Panel B: 1991-2003

Dependent variable:	Daily volatility (q) (%)						
Subperiod	1991-2003						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	1.363***	1.861***	1.978***	2.124***	1.493***	1.374***	1.038***
	(3.967)	(5.717)	(6.045)	(7.168)	(5.931)	(5.193)	(5.243)
Ownership by "middle" institutions	0.662***	0.603***	0.555***	0.473***	0.410***	0.463***	0.481***
	(6.170)	(5.569)	(5.420)	(4.566)	(3.855)	(4.497)	(4.474)
1 / price (q-1)	1.021***	1.021***	1.020***	1.019***	1.022***	1.023***	1.023***
	(7.180)	(7.175)	(7.166)	(7.166)	(7.199)	(7.203)	(7.204)
Amihud illiquidity (q-1)	1.348***	1.346***	1.345***	1.343***	1.348***	1.351***	1.352***
	(13.320)	(13.305)	(13.279)	(13.266)	(13.325)	(13.365)	(13.390)
log(market cap) (q-1)	-0.334***	-0.339***	-0.342***	-0.347***	-0.311***	-0.308***	-0.307***
	(-8.067)	(-8.216)	(-8.181)	(-8.366)	(-7.991)	(-7.807)	(-7.858)
Past 6-month return (q-3 to q-1)	-0.096	-0.095	-0.093	-0.090	-0.100	-0.102	-0.102
	(-0.623)	(-0.616)	(-0.605)	(-0.586)	(-0.646)	(-0.658)	(-0.659)
Book-to-market (q-1)	-0.129***	-0.130***	-0.130***	-0.131***	-0.127***	-0.129***	-0.127***
	(-4.285)	(-4.320)	(-4.322)	(-4.343)	(-4.229)	(-4.249)	(-4.224)
Ownership by bottom institutions (q-1)	-1.191***	-1.169***	-1.150***	-1.130***	-1.212***	-1.219***	-1.218***
	(-3.304)	(-3.256)	(-3.191)	(-3.159)	(-3.374)	(-3.389)	(-3.388)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	291,030	291,030	291,030	291,030	291,030	291,030	291,030
Adj R^2	0.712	0.713	0.713	0.713	0.712	0.712	0.712

Panel C: 2004-2016

Dependent variable:	Daily volatility (q) (%)						
Subperiod	2004-2016						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	2.030***	1.961***	1.515***	1.262***	1.077***	0.439**	0.240
	(6.228)	(6.953)	(6.990)	(7.943)	(5.561)	(2.132)	(1.028)
Ownership by "middle" institutions	0.269***	0.190**	0.201**	0.216***	0.117	0.212**	0.225**
	(3.407)	(2.372)	(2.553)	(2.703)	(1.442)	(2.667)	(2.496)
1 / price (q-1)	0.677***	0.673***	0.671***	0.671***	0.669***	0.670***	0.670***
	(8.901)	(8.861)	(8.856)	(8.867)	(8.906)	(8.898)	(8.914)
Amihud illiquidity (q-1)	0.892***	0.888***	0.888***	0.889***	0.890***	0.889***	0.889***
	(14.436)	(14.447)	(14.477)	(14.428)	(14.364)	(14.389)	(14.401)
log(market cap) (q-1)	-0.491***	-0.501***	-0.497***	-0.495***	-0.460***	-0.458***	-0.458***
	(-9.462)	(-9.450)	(-9.467)	(-9.594)	(-9.307)	(-9.273)	(-9.275)
Past 6-month return (q-3 to q-1)	-0.010	-0.005	-0.007	-0.007	-0.020	-0.024	-0.024
	(-0.161)	(-0.083)	(-0.110)	(-0.114)	(-0.310)	(-0.363)	(-0.360)
Book-to-market (q-1)	0.161***	0.158***	0.160***	0.160***	0.163***	0.164***	0.164***
	(6.034)	(5.924)	(5.971)	(6.015)	(6.127)	(6.184)	(6.208)
Ownership by bottom institutions (q-1)	-1.160***	-1.132***	-1.164***	-1.168***	-1.295***	-1.309***	-1.309***
	(-6.359)	(-6.286)	(-6.413)	(-6.390)	(-7.137)	(-7.187)	(-7.195)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218,182	218,182	218,182	218,182	218,182	218,182	218,182
Adj R^2	0.673	0.673	0.673	0.672	0.672	0.672	0.672

Table 4. Stock Volatility around Mergers of Large Institutions

The dependent variable is the daily volatility of the stocks held by large institutional investors in the next quarter. *Daily volatility* is computed from daily returns. We use the exogenous event of the merger between BlackRock and BGI in 2009/Q4 to test the relation between volatility and ownership by large institutions. The key independent variable is the interaction term *Treatment×Post-Merger Dummy*, where *Treatment* represents the ownership of Blackrock as of 2009/Q3, i.e., before the merger was completed , and *Post-merger dummy* equals 1 for 2010/Q1 and later quarters. In Panel A, the treatement variable is the level of ownership. In Panel B, it is an indicator for ownership in the top half of the distribution. In Panel C, ownership is again a continuous variable, but we skip the first year after the merger. The sample in each column includes 2007/Q4-2009/Q4 plus several quarters after the completion, as specified in the heading. *t*-statistics based on bootstrapped standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Treatment is the Level of Ownership

Dependent variable:	Daily volatility (q) (%)							
Treatment:	Ownership by Blackrock: Q3, 2009							
Window after merger:	+1 qtr	+2 qtrs	+3 qtrs	+4 qtrs	+5 qtrs	+6 qtrs	+7 qtrs	+8 qtrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post Merger Dummy	3.610**	4.528***	3.113***	2.582**	2.778***	3.057***	4.012***	4.270***
	(2.405)	(4.192)	(3.105)	(2.302)	(3.055)	(3.166)	(4.234)	(3.828)
Ownership by all institutions (q-1)	0.980***	0.995***	1.033***	0.986***	0.887***	0.814***	0.812***	0.823***
	(6.654)	(7.462)	(7.485)	(7.664)	(7.049)	(7.151)	(7.508)	(7.586)
1 / price (q-1)	0.203***	0.247***	0.281***	0.321***	0.341***	0.368***	0.396***	0.417***
	(4.423)	(4.202)	(5.568)	(5.877)	(7.047)	(7.015)	(8.679)	(9.248)
Amihud illiquidity (q-1)	0.872***	0.864***	0.871***	0.864***	0.872***	0.867***	0.901***	0.894***
	(19.810)	(16.759)	(15.760)	(15.318)	(18.083)	(17.547)	(20.112)	(18.231)
log(market cap) (q-1)	-0.969***	-0.908***	-0.844***	-0.787***	-0.735***	-0.672***	-0.598***	-0.596***
	(-19.569)	(-24.126)	(-25.803)	(-21.940)	(-23.126)	(-21.671)	(-17.931)	(-18.760)
Past 6-month return (q-3 to q-1)	-0.076***	-0.074***	-0.081***	-0.084***	-0.072***	-0.067***	-0.073***	-0.079***
	(-3.344)	(-4.358)	(-3.480)	(-4.301)	(-3.836)	(-3.190)	(-4.990)	(-3.712)
Book-to-market (q-1)	-0.040**	-0.027	-0.002	0.011	0.024	0.043**	0.055***	0.055***
	(-2.044)	(-1.542)	(-0.082)	(0.552)	(1.107)	(2.422)	(3.054)	(3.007)
Ownership by bottom institutions (q-1)	0.212	0.131	0.027	-0.026	-0.101	-0.148	-0.256	-0.347**
	(0.970)	(0.610)	(0.144)	(-0.114)	(-0.523)	(-0.740)	(-1.627)	(-2.095)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,266	40,944	44,603	48,241	51,710	55,151	58,550	61,876
Adj R^2	0.576	0.568	0.565	0.569	0.571	0.574	0.563	0.552

Table 4. Volatility of Firms around Mergers of Large Institutions (Cont.)

Panel B: Treatment is Top 50% Ownership Indicator

Dependent variable:	Daily volatility (q) (%)							
Treatment:	Ownership by Blackrock: Q3, 2009							
Window after merger:	+1 qtr	+2 qtrs	+3 qtrs	+4 qtrs	+5 qtrs	+6 qtrs	+7 qtrs	+8 qtrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post Merger Dummy	0.129***	0.188***	0.158***	0.154***	0.169***	0.179***	0.226***	0.251***
	(3.277)	(5.565)	(5.359)	(4.835)	(6.271)	(5.759)	(7.758)	(7.778)
Ownership by all institutions (q-1)	0.981***	0.992***	1.030***	0.982***	0.886***	0.817***	0.819***	0.833***
	(6.529)	(7.937)	(8.021)	(6.818)	(6.882)	(7.418)	(8.019)	(9.871)
1 / price (q-1)	0.203***	0.248***	0.281***	0.320***	0.340***	0.367***	0.395***	0.415***
	(4.089)	(4.819)	(6.196)	(6.214)	(6.981)	(7.599)	(7.070)	(8.186)
Amihud illiquidity (q-1)	0.870***	0.856***	0.860***	0.852***	0.856***	0.848***	0.876***	0.866***
	(20.326)	(17.614)	(18.440)	(20.605)	(17.232)	(18.588)	(17.504)	(21.339)
log(market cap) (q-1)	-0.973***	-0.917***	-0.853***	-0.797***	-0.747***	-0.686***	-0.616***	-0.615***
	(-24.873)	(-26.720)	(-23.558)	(-21.708)	(-19.273)	(-19.861)	(-19.153)	(-22.143)
Past 6-month return (q-3 to q-1)	-0.074***	-0.070***	-0.077***	-0.079***	-0.066***	-0.061***	-0.065***	-0.071***
	(-3.235)	(-3.095)	(-4.357)	(-3.960)	(-3.413)	(-3.529)	(-3.565)	(-4.071)
Book-to-market (q-1)	-0.041**	-0.027	-0.002	0.011	0.023*	0.042**	0.054***	0.053***
	(-2.108)	(-1.250)	(-0.083)	(0.523)	(1.655)	(2.415)	(3.271)	(2.861)
Ownership by bottom institutions (q-1)	0.223	0.161	0.062	0.009	-0.059	-0.099	-0.193	-0.273
	(1.084)	(0.678)	(0.279)	(0.044)	(-0.308)	(-0.534)	(-0.947)	(-1.202)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,266	40,944	44,603	48,241	51,710	55,151	58,550	61,876
Adj R^2	0.576	0.568	0.565	0.570	0.571	0.574	0.563	0.553

Panel C: Continuous Treatment, Omitting the First Year after Merger Completion

Dependent variable:	Daily volatility (q) (%)			
Treatment:	Ownership by Blackrock: Q3, 2009			
Window after merger:	+5 qtrs	+6 qtrs	+7 qtrs	+8 qtrs
	(1)	(2)	(3)	(4)
Treatment × Post-Merger Dummy	4.608***	4.978***	7.147***	6.958***
	(3.080)	(3.318)	(5.101)	(5.367)
Ownership by all institutions (q-1)	0.819***	0.747***	0.775***	0.799***
	(5.722)	(5.723)	(6.438)	(6.682)
1 / price (q-1)	0.227***	0.284***	0.329***	0.360***
	(4.776)	(5.720)	(5.806)	(6.940)
Amihud illiquidity (q-1)	0.899***	0.890***	0.931***	0.923***
	(18.697)	(16.354)	(17.612)	(18.241)
log(market cap) (q-1)	-0.898***	-0.764***	-0.642***	-0.625***
	(-24.538)	(-17.133)	(-19.464)	(-16.449)
Past 6-month return (q-3 to q-1)	-0.067***	-0.081***	-0.098***	-0.107***
	(-3.672)	(-5.092)	(-4.965)	(-6.044)
Book-to-market (q-1)	-0.033	0.004	0.028	0.034
	(-1.453)	(0.195)	(1.450)	(1.640)
Ownership by bottom institutions (q-1)	0.124	0.022	-0.138	-0.256
	(0.603)	(0.107)	(-0.663)	(-1.465)
Stock FE	Yes	Yes	Yes	Yes
Calendar Quarter FE	Yes	Yes	Yes	Yes
Observations	37,015	40,456	43,855	47,181
Adj R^2	0.579	0.588	0.573	0.561

Table 5. Large Institutional Ownership and Return Autocorrelation

This table presents ordinary least squares regression results. In Panels A and D, the dependent variable is the absolute value of *autocorrelation* of the DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers 1997) of stocks held by large institutional investors. In Panel C, the dependent variable is the signed *autocorrelation* of DGTW-adjusted returns. In all panels, the key independent variable is the *Ownership* of the top institutions in the previous quarter. Panels B and C examine *autocorrelation* around the Blackrock-BGI merger. In Panel A, the sample period is 1980/Q1–2016/Q4. In Panels B-C, the sample period is 2007/Q4-2011/Q4. *t*-statistics based on standard errors clustered at the stock and quarter level are in parentheses (Panels A-C). For Panels B-C, standard errors are bootstrapped. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Absolute Value of Autocorrelation

Dependent variable:	ABS(ρ(DGTW-adjusted returns)) (q)						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	0.028***	0.021**	0.014**	0.022***	0.004	-0.022**	-0.011*
	(2.854)	(2.518)	(2.014)	(3.233)	(0.596)	(-2.402)	(-1.754)
Ownership by "middle" institutions	-0.020***	-0.020***	-0.021***	-0.024***	-0.026***	-0.026***	-0.028***
	(-7.394)	(-7.661)	(-7.696)	(-8.430)	(-8.713)	(-8.731)	(-8.854)
1 / price (q-1)	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-10.063)	(-10.079)	(-10.097)	(-10.120)	(-10.119)	(-10.116)	(-10.136)
Amihud illiquidity (q-1)	0.064***	0.064***	0.064***	0.064***	0.064***	0.064***	0.064***
	(31.256)	(31.198)	(31.149)	(31.193)	(31.269)	(31.268)	(31.267)
log(market cap) (q-1)	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-8.584)	(-8.625)	(-8.606)	(-8.930)	(-8.799)	(-8.945)	(-9.212)
Past 6-month return (q-3 to q-1)	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-6.364)	(-6.332)	(-6.344)	(-6.265)	(-6.290)	(-6.302)	(-6.232)
Book-to-market (q-1)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-3.850)	(-3.885)	(-3.850)	(-3.867)	(-3.743)	(-3.748)	(-3.828)
Ownership by bottom institutions (q-1)	-0.017**	-0.016*	-0.017*	-0.015*	-0.017*	-0.017*	-0.017*
	(-2.018)	(-1.912)	(-1.949)	(-1.735)	(-1.948)	(-1.964)	(-1.944)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	591,089	591,089	591,089	591,089	591,089	591,089	591,089
Adj R^2	0.284	0.284	0.284	0.284	0.284	0.284	0.284

Table 5. Large Institutional Ownership and Return Autocorrelation (Cont.)

Panel B: Absolute Value Autocorrelation around the Blackrock-BGI Merger

Dependent variable:	ABS(ρ(DGTW-adjusted returns)) (q)							
Treatment:	Ownership by BlackRock Q3, 2009							
Window after merger:	+1 qtr	+2 qtrs	+3 qtrs	+4 qtrs	+5 qtrs	+6 qtrs	+7 qtrs	+8 qtrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post-Merger Dummy	0.021***	0.016***	0.013***	0.016***	0.017***	0.015***	0.013***	0.013***
	(7.530)	(6.673)	(6.024)	(7.366)	(8.059)	(7.628)	(6.736)	(6.734)
Ownership by all institutions (q-1)	-0.030***	-0.029***	-0.022***	-0.024***	-0.024***	-0.023***	-0.024***	-0.025***
	(-3.351)	(-3.504)	(-2.877)	(-3.411)	(-3.630)	(-3.690)	(-4.005)	(-4.466)
1 / price (q-1)	-0.008**	-0.008***	-0.007**	-0.008***	-0.008***	-0.007***	-0.006**	-0.005**
	(-2.567)	(-2.678)	(-2.535)	(-3.006)	(-3.037)	(-2.882)	(-2.440)	(-2.286)
Amihud illiquidity (q-1)	0.026***	0.027***	0.027***	0.029***	0.030***	0.031***	0.031***	0.031***
	(8.078)	(8.707)	(9.014)	(9.966)	(10.838)	(11.632)	(11.801)	(12.322)
log(market cap) (q-1)	-0.002	-0.003	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(-0.845)	(-1.401)	(-0.539)	(-0.317)	(-0.617)	(-0.911)	(-0.863)	(-1.144)
Past 6-month return (q-3 to q-1)	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.372)	(-0.383)	(-0.443)	(-0.378)	(-0.174)	(-0.200)	(-0.063)	(0.306)
Book-to-market (q-1)	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(-3.353)	(-3.798)	(-3.797)	(-3.940)	(-4.112)	(-4.466)	(-4.260)	(-4.711)
Ownership by bottom institutions (q-1)	0.049*	0.038	0.041	0.046**	0.043**	0.030	0.030	0.034*
	(1.690)	(1.408)	(1.636)	(2.017)	(2.039)	(1.458)	(1.525)	(1.792)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,083	36,696	40,313	43,813	47,261	50,638	53,941	57,189
Adj R^2	0.329	0.318	0.307	0.296	0.286	0.277	0.273	0.270

Panel C: Signed Autocorrelation around the Blackrock-BGI Merger

Dependent variable:	ρ(DGTW-adjusted returns) (q)							
Treatment:	Ownership by BlackRock Q3, 2009							
Window after merger:	+1 qtr	+2 qtrs	+3 qtrs	+4 qtrs	+5 qtrs	+6 qtrs	+7 qtrs	+8 qtrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post-Merger Dummy	-0.017***	-0.012***	-0.009***	-0.016***	-0.017***	-0.014***	-0.013***	-0.013***
	(-4.083)	(-3.320)	(-2.857)	(-5.263)	(-5.662)	(-4.715)	(-4.475)	(-4.665)
Ownership by all institutions (q-1)	0.050***	0.053***	0.048***	0.053***	0.052***	0.050***	0.048***	0.044***
	(3.654)	(4.240)	(4.035)	(4.867)	(5.197)	(5.253)	(5.394)	(5.167)
1 / price (q-1)	0.009**	0.010**	0.007*	0.007*	0.006	0.006	0.004	0.003
	(2.147)	(2.426)	(1.829)	(1.815)	(1.627)	(1.622)	(1.062)	(0.917)
Amihud illiquidity (q-1)	-0.039***	-0.040***	-0.039***	-0.040***	-0.042***	-0.043***	-0.042***	-0.042***
	(-9.482)	(-10.329)	(-10.520)	(-11.253)	(-12.115)	(-12.849)	(-13.034)	(-13.649)
log(market cap) (q-1)	-0.001	0.002	-0.002	-0.004	-0.004	-0.001	-0.000	0.001
	(-0.176)	(0.641)	(-0.689)	(-1.309)	(-1.371)	(-0.352)	(-0.064)	(0.291)
Past 6-month return (q-3 to q-1)	-0.004*	-0.005**	-0.004**	-0.004*	-0.004**	-0.004*	-0.004**	-0.005***
	(-1.900)	(-2.309)	(-2.188)	(-1.896)	(-2.124)	(-1.956)	(-2.343)	(-2.655)
Book-to-market (q-1)	0.006***	0.007***	0.007***	0.007***	0.007***	0.008***	0.008***	0.008***
	(3.547)	(4.128)	(4.078)	(4.142)	(4.404)	(4.997)	(4.934)	(5.368)
Ownership by bottom institutions (q-1)	-0.076*	-0.085**	-0.100***	-0.085**	-0.068**	-0.059*	-0.062**	-0.060**
	(-1.828)	(-2.207)	(-2.791)	(-2.508)	(-2.135)	(-1.941)	(-2.154)	(-2.174)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,083	36,696	40,313	43,813	47,261	50,638	53,941	57,189
Adj R^2	0.352	0.341	0.332	0.321	0.312	0.306	0.301	0.298

Table 6. Ownership by Large Institutional Investors and Stock Returns during Periods of Market Turmoil

This table presents ordinary least squares regression results. The dependent variable is the quarterly *DGTW Excess Return* (Daniel, Grinblatt, Titman, and Wermers 1997) of stocks held by large institutional investors. All independent variables are measured during quarter q-1. The table uses the *Top inst. ownership* of the largest institutional investors in a given stock as the key independent variable. *Top inst. ownership* is interacted with a dummy variable that equals one if the market was in the 5% left tail of returns during a particular quarter. The sample period is 1980/Q1–2016/Q4. *t*-statistics based on standard errors clustered at the stock and quarter level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	DGTW Excess Returns (Quarterly)						
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 11-20	Top 21-30	Top 31-50
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top inst ownership (q-1)	-0.001	0.000	0.006	0.005	0.002	0.015	-0.014
	(-0.073)	(0.028)	(0.593)	(0.511)	(0.367)	(1.470)	(-1.540)
Top inst ownership (q-1) × Bottom 5% Dummy	-0.175*	-0.171**	-0.173**	-0.191***	0.012	-0.001	0.097**
	(-1.728)	(-2.341)	(-2.448)	(-2.966)	(0.329)	(-0.015)	(2.318)
Ownership by "middle" institutions	0.006*	0.006*	0.006*	0.006*	0.006*	0.005	0.007**
	(1.955)	(1.953)	(1.735)	(1.754)	(1.848)	(1.598)	(2.234)
Ownership by "middle" institutions × Bottom 5% Dummy	-0.020	-0.016	-0.013	-0.006	-0.015	-0.012	-0.020
	(-1.091)	(-0.864)	(-0.738)	(-0.331)	(-0.793)	(-0.584)	(-1.015)
1 / price (q-1)	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(-4.204)	(-4.204)	(-4.204)	(-4.205)	(-4.206)	(-4.213)	(-4.194)
1 / price (q-1) × Bottom 5% Dummy	-0.016	-0.016	-0.016	-0.016	-0.015	-0.015	-0.015
	(-1.550)	(-1.516)	(-1.515)	(-1.494)	(-1.405)	(-1.399)	(-1.439)
Amihud illiquidity (q-1)	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.623)	(-1.618)	(-1.635)	(-1.632)	(-1.607)	(-1.617)	(-1.624)
Amihud illiquidity (q-1) × Bottom 5% Dummy	0.001	0.001	0.001	0.002	0.000	0.001	0.001
	(0.092)	(0.081)	(0.104)	(0.149)	(0.034)	(0.052)	(0.072)
log(market cap) (q-1)	-0.020***	-0.020***	-0.020***	-0.020***	-0.020***	-0.020***	-0.020***
	(-20.105)	(-19.997)	(-20.140)	(-20.085)	(-20.535)	(-20.525)	(-20.425)
log(market cap) (q-1) × Bottom 5% Dummy	0.008**	0.008**	0.008**	0.009**	0.005	0.005	0.005
	(2.170)	(2.275)	(2.379)	(2.595)	(1.492)	(1.489)	(1.461)
Past 6-month return (q-3 to q-1)	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*	0.003*
	(1.692)	(1.689)	(1.697)	(1.692)	(1.678)	(1.687)	(1.665)
Past 6-month return (q-3 to q-1) × Bottom 5% Dummy	-0.029**	-0.029**	-0.029**	-0.030**	-0.029**	-0.029**	-0.029**
	(-2.450)	(-2.451)	(-2.468)	(-2.492)	(-2.431)	(-2.440)	(-2.446)
Book-to-market (q-1)	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(2.026)	(2.031)	(2.021)	(2.022)	(2.032)	(2.025)	(2.065)
Book-to-market (q-1) × Bottom 5% Dummy	0.004	0.004	0.004	0.004	0.003	0.003	0.003
	(0.559)	(0.607)	(0.594)	(0.565)	(0.472)	(0.475)	(0.436)
Ownership by bottom institutions (q-1)	0.068***	0.068***	0.068***	0.068***	0.067***	0.067***	0.067***
	(5.248)	(5.251)	(5.253)	(5.235)	(5.124)	(5.117)	(5.127)
Ownership by bottom institutions (q-1) × Bottom 5% Dummy	-0.031	-0.035	-0.035	-0.041	-0.015	-0.015	-0.018
	(-0.388)	(-0.428)	(-0.434)	(-0.500)	(-0.178)	(-0.179)	(-0.211)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	479,839	479,839	479,839	479,839	479,839	479,839	479,839
Adj R^2	0.080	0.080	0.080	0.080	0.080	0.080	0.080

Table 7. Correlation of Fund Flows and Similarities in Holdings and Trades

The table presents tests for whether mutual funds within the same family have correlated flows, returns, and similar portfolio holdings and trades. All panels present results from ordinary least squares regressions on an indicator for membership of the funds in the same family. In Panel A, for each fund pair-year, we compute the 12-month correlation of flows (scaled by lagged total net assets) over the calendar year. The dependent variable is the correlation between each pair of funds. In Panel B, we compute the 12-month correlation of the active trades of two funds over the calendar year. The dependent variable is the correlation of active trades between each pair of funds. In all panels, we use a random sample of 1% of all observations to generate regressions (1)-(4) for computational efficiency. *t*-statistics in parentheses are based on standard errors with three-way clustering: year, fund i, and fund j. The sample period is 1980/Q1–2016/Q4. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Correlation of Fund Flows within the Same Family

Dependent Variable:	Correlation of Flows between Fund i and Fund j							
	All Institutions				Top 20 Institutions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same management company (i,j)	0.032***	0.032***	0.032***	0.032***	0.022***	0.024***	0.024***	0.024***
	(8.082)	(10.448)	(10.477)	(10.668)	(4.528)	(6.323)	(6.364)	(7.230)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Fund i, Fund j FE	No	Yes	Yes	No	No	Yes	Yes	No
Year × Fund i FE, Year × Fund j FE	No	No	No	Yes	No	No	No	Yes
Observations	2,338,212	2,338,136	2,338,135	2,335,052	612,325	612,253	612,252	603,302
Adj R^2	0.002	0.022	0.024	0.161	0.003	0.037	0.040	0.270

Panel B: Correlation in Active Trades within the Same Family

Dependent Variable:	Correlation of active trades between Fund i and Fund j							
	All Institutions				Top 20 Institutions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same management company (i,j)	0.029***	0.026***	0.026***	0.025***	0.025***	0.022***	0.022***	0.022***
	(13.533)	(13.157)	(12.979)	(12.013)	(9.060)	(8.872)	(8.788)	(7.566)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Fund i, Fund j FE	No	Yes	Yes	No	No	Yes	Yes	No
Year × Fund i FE, Year × Fund j FE	No	No	No	Yes	No	No	No	Yes
Observations	1,265,379	1,265,253	1,265,253	1,260,278	330,551	330,449	330,449	321,488
Adj R^2	0.006	0.061	0.064	0.233	0.008	0.093	0.099	0.378

Table 8. Correlation of Flows and Trades around the BlackRock-BGI Merger

In Panel A, the dependent variable is the correlation of flows between fund *i* and fund *j*, and in Panel B the dependent variable is the correlation of the change in holdings between fund *i* and fund *j*. For each fund pair-year, we compute the 12-month *correlation* of flows (scaled by lagged total net assets) over the calendar year. We use the exogenous event of the merger between BlackRock and BGI in 2009 to test the relation between flow or holding changes correlation and ownership by large institutions. The *Treatment* dummy identifies funds that before the merger were in separate asset management firms (either BGI or BlackRock). The annual sample ranges between 2008 and 2011. The *Post-merger dummy* identifies the years 2010 and 2011. We also include a dummy for pairs of funds that were in the same company (either BlackRock or BGI) before the merger (*BlackRock or BGI Pair*). *t*-statistics based on bootstrapped standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fund flow correlation around the Blackrock-BGI merger

Dependent Variable:	Correlation of Flows between Fund i and Fund j			
	(1)	(2)	(3)	(4)
Treatment × Post-Merger Dummy	0.043***	0.043***	0.043***	0.043***
	(5.949)	(5.995)	(5.955)	(5.983)
Treatment Dummy	-0.028***	-0.015**	-0.028***	-0.015**
	(-4.656)	(-2.459)	(-4.691)	(-2.449)
Post × Blackrock or BGI Pair	0.059***	0.061***	0.058***	0.061***
	(4.907)	(5.165)	(4.902)	(5.125)
Blackrock or BGI Pair	-0.000	0.004	-0.000	0.005
	(-0.018)	(0.501)	(-0.033)	(0.533)
Post-Merger Dummy	-0.009***	-0.011***		
	(-4.614)	(-5.346)		
Constant	0.044***			
	(25.995)			
Fund i, Fund j FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Observations	28,022,747	28,022,747	28,022,747	28,022,747
Adj R^2	0.000	0.044	0.001	0.045

Panel B: Holding changes correlation around the Blackrock-BGI merger

Dependent Variable:	Correlation of change in holdings between Fund i and Fund j			
	(1)	(2)	(3)	(4)
Treatment × Post-Merger Dummy	0.003*	0.004***	0.003*	0.004***
	(1.752)	(9.731)	(1.730)	(7.273)
Treatment Dummy	-0.008***	-0.003**	-0.008***	-0.003**
	(-3.872)	(-2.259)	(-3.725)	(-2.130)
Post × Blackrock or BGI Pair	0.002*	0.003***	0.002*	0.003**
	(1.930)	(3.310)	(1.837)	(2.566)
Blackrock or BGI Pair	-0.009***	-0.003**	-0.009***	-0.003**
	(-8.874)	(-2.155)	(-8.479)	(-1.972)
Post-Merger Dummy	-0.005***	-0.005***		
	(-16.220)	(-15.393)		
Constant	0.012***			
	(31.499)			
Fund i, Fund j FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
Observations	27,519,752	27,519,752	27,519,752	27,519,752
Adj R^2	0.000	0.008	0.001	0.008

Table 9. Comparison to Synthetic Institutions: Small Universe and Large Trades

The table compares the portfolio holdings and trade sizes of large institutional investors to synthetic institutional investors. For each top-10 institutional investor and quarter, we create 99 synthetic institutions composed of smaller institutions that together equal the size (assets under management) of the top institution. Then, we sort the portfolio holdings (stocks) by their value in the portfolio and count how many stocks make a certain fraction of the portfolio value. We compare these numbers to the number of stocks held by the original institutional investors that make up the same portfolio fraction. Panel A presents the average number of stocks held in the original portfolio relative to the number of stocks held in the synthetic portfolio. In Panel B, we compare the size of the trades of large institutions to those of synthetic institutions. For each stock-quarter within a portfolio, we calculate the change in the value of portfolio holdings since the last quarter. Then, for each institution-quarter, we calculate the percentage of trades that have a larger absolute value than a certain percentile in the distribution of trade sizes by the synthetic institutions. The panel shows the average percentage of trades by large institutional investors that are above the 50th, 90th, 95th, and 99th percentiles of the distribution of trades of the synthetic institutions.

Panel A: Number of Stocks Contained in the Portfolios of Large Institutional Investors

	Average number of stocks that make up X% of the equity porfolio													
	100%		99%		90%		80%		70%		60%		50%	
Institutional investor	Orig.	Synth.	Orig.	Synth.	Orig.	Synth.	Orig.	Synth.	Orig.	Synth.	Orig.	Synth.	Orig.	Synth.
Top 1	2,836	3,056	1,658	1,634	637	654	339	370	205	230	128	147	79	93
Top 2	2,736	2,843	1,543	1,537	555	620	304	352	187	219	118	141	73	90
Top 3	2,202	2,702	1,235	1,480	409	603	233	343	147	214	94	137	60	88
Top 4	2,044	2,646	1,156	1,453	416	592	235	338	149	211	97	135	62	87
Top 5	1,571	2,491	937	1,376	379	562	221	321	144	201	95	129	62	83
Top 6	1,607	2,407	889	1,332	342	545	194	312	124	196	81	126	53	81
Top 7	1,562	2,422	873	1,342	336	549	194	314	124	197	82	127	54	81
Top 8	1,766	2,394	975	1,325	376	543	211	311	132	195	85	126	55	81
Top 9	1,682	2,283	966	1,270	363	523	203	301	127	189	81	122	52	79
Top 10	1,922	2,240	1,055	1,248	381	515	211	296	132	186	85	120	56	77
Average	1,995	2,550	1,130	1,401	420	571	235	326	147	204	95	131	61	84
Difference	-28%		-24%		-36%		-39%		-38%		-38%		-38%	

Panel B: Trades by Large Institutional Investors Relative to Trades by Synthetic Institutions

	%Stock-quarter with abs(trade) of top institutions			
	> 50th pctile	> 90th pctile	> 95th pctile	> 99th pctile
	(1)	(2)	(3)	(4)
Top 1	52.7%	14.8%	8.5%	4.3%
Top 2	51.3%	12.4%	6.7%	3.3%
Top 3	45.7%	12.9%	7.7%	3.4%
Top 4	57.2%	17.1%	9.7%	4.1%
Top 5	53.6%	15.7%	9.1%	3.5%
Top 6	57.8%	18.3%	10.6%	4.0%
Top 7	62.6%	21.0%	12.6%	4.7%
Top 8	59.4%	15.9%	9.0%	3.2%
Top 9	60.5%	16.8%	9.8%	3.5%
Top 10	60.1%	17.1%	9.9%	3.5%
Average	56.1%	16.2%	9.4%	3.7%

Appendix. Top Institutional Investors

This table lists all the institutional investors that enter the top-10-institution ranking during our sample period. *First Quarter* and *Last Quarter* indicate the first and last quarter in which the firm is part of the ranking, respectively. *Avg Long Equity Assets* is the average assets managed by the institution over the time that the institution is in our sample, defined in 2016 dollars. *Avg Quarterly Turnover* measures the percentage of assets under management that are bought and sold within the average quarter. *Top Rank* is the average ranking of the firm's size relative to all other institutional investors while it is among the top 10 institutions.

13F Institution Name	13F Institution Number	Zip Code	State	Number of Quarters	First Quarter	Last Quarter	Avg Long Equity Assets ($m)	Avg Quarterly Turnover	Top Rank
Bzw Barclays Glbl Invts	92040	94105	CA	24	6-1990	3-1996	$78,571.35	2.17%	1.3
Barclays Bank Plc	7900	94104	CA	51	3-1997	9-2009	$480,174.61	5.02%	1.6
Blackrock Inc	9385	94105	CA	29	12-2009	12-2016	$1,135,744.36	5.12%	1.6
Fidelity Mgmt & Research Co	27800	02109	MA	101	12-1991	12-2016	$439,065.33	12.08%	2.2
Fmr Corp	26590	02109	MA	20	3-1986	12-1990	$27,215.97	18.63%	3.7
Bankers Tr N Y Corp (Deutsche Bk)	7800	10017	NY	95	3-1980	6-2005	$75,098.19	5.93%	3.8
State Str Corporation	81540	02111	MA	111	6-1988	12-2016	$361,727.25	4.49%	4.1
Vanguard Group, Inc.	90457	19482	PA	72	3-1999	12-2016	$563,593.76	2.28%	4.3
Wells Fargo Bank N.A.	92035	94104	CA	37	6-1980	3-1990	$22,942.46	5.59%	4.5
Prudential Ins Co/Amer	72280	07102	NJ	15	3-1980	9-1983	$6,962.83	10.73%	4.7
College Retire Equities	18265	10017	NY	74	3-1980	6-1998	$32,609.23	4.51%	4.7
Capital Research & Mgmt Co	12740	90071	CA	72	9-1990	6-2008	$214,521.95	7.93%	4.9
Manufacturers Natl	53690	48226	MI	1	3-1980	3-1980	$4,623.67	.	5.0
Batterymarch Finl Mgmt	8190	02116	MA	18	12-1981	3-1986	$9,479.47	10.97%	5.7
Equitable Companies Inc (Axa)	25610	10014	NY	63	6-1994	12-2009	$199,440.25	11.83%	6.0
T. Rowe Price Associates, Inc.	71110	21202	MD	48	3-1980	12-2016	$253,372.00	8.18%	6.2
Donaldson Lufkin & Jen	23375	10172	NY	13	12-1982	12-1985	$10,347.28	18.18%	6.2
Citicorp	16260	10022	NY	28	3-1980	3-1988	$8,883.59	10.96%	6.3
Alliance Capital Mgmt	1250	10105	NY	27	12-1986	6-1993	$23,161.08	13.11%	6.4
JP Morgan Chase & Company	58835	10017	NY	86	3-1980	12-2016	$93,986.95	10.15%	6.5
Capital World Investors	11836	90071	CA	37	12-2007	12-2016	$290,515.76	7.81%	6.6
Mellon National Corp (Mellon Bank)	55390	15219	PA	117	3-1980	3-2013	$118,351.34	7.03%	6.7
Putnam Investment Mgmt, L.L.C.	72400	02266	MA	42	9-1980	9-2003	$122,707.37	14.41%	7.4
First Interstate Bancorp	29800	90017	CA	19	6-1981	3-1987	$10,720.55	7.32%	7.5
Sarofim Fayez	76045	77010	TX	10	12-1980	3-1983	$6,013.41	7.12%	7.7
BANK OF AMERICA CORP /DE/	62890	28255	NC	5	12-2015	12-2016	$360,834.33	6.65%	7.8
State Street Resr & Mgmt	81575	02111	MA	12	6-1982	3-1985	$7,741.61	7.89%	7.8
Wellington Management Co, LLP	91910	02210	MA	102	6-1985	12-2016	$170,432.81	10.97%	8.0
Bank of New York Mellon Corp	12276	10286	NY	12	3-2014	12-2016	$330,441.69	5.02%	8.2
New York St Common Ret.	63850	10038	NY	30	12-1986	3-1994	$21,270.73	3.99%	8.2
Calif Public Emp. Ret.	12000	95811	CA	4	12-1988	9-1989	$16,805.40	8.20%	8.3
Capital Research Gbl Investors	11835	90071	CA	24	12-2007	12-2013	$224,601.66	8.52%	8.5
Harris Trust & Sav Bank	43680	60640	IL	3	3-1980	9-1980	$4,557.99	8.37%	8.7
Janus Capital Corporation	48170	80206	CO	5	3-2000	3-2001	$189,638.67	15.17%	8.8
Calif Public Empl Retirm	12090	95811	CA	5	6-1986	12-1987	$15,388.04	5.87%	9.4
Morgan Stanley D Witter	58950	10036	NY	22	12-1997	3-2011	$172,554.96	10.59%	9.4
Travelers (Citigroup Inc)	84900	55102 (10022)	MN (NY)	17	6-1996	9-2005	$144,162.92	9.35%	9.4
Legg Mason Inc	50160	21202	MD	4	9-2006	6-2007	$211,065.84	7.09%	9.5
Northern Trust Corp	65260	60603	IL	22	12-2003	9-2015	$234,466.52	3.02%	9.7
Chase Manhattan Corp	15230	10017	NY	2	3-1980	6-1980	$4,221.70	4.20%	10.0
Goldman Sachs & Company	41260	10282	NY	1	9-2007	9-2007	$236,162.71	17.58%	10.0