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ABSTRACT

Over the last four decades, the concentration of institutional assets in equity markets has increased dramatically. We conjecture that large institutions are granular, that is, they cannot be reduced to a collection of smaller independent entities. Hence, the paper studies whether large institutional ownership has a significant impact on asset prices. We provide evidence of a causal effect of ownership by large institutions on the volatility of their stock holdings. As a potential channel for this effect, we show that large institutions generate higher price impact than smaller institutions. Their trades are larger and concentrated on fewer stocks than those of smaller firms. Moreover, the investor flows to units within the same family are more correlated than the flows to independent entities. Finally, the effect of large institutions on volatility is unlikely to be related to improved price discovery, because the stocks owned by large institutions exhibit stronger price inefficiency.

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1 Introduction

The U.S. asset management industry has become increasingly concentrated in recent times. Over the last 35 years, the largest institutional investors have quadrupled their holdings in the equity market. As of September 2015, the largest asset manager oversaw 5.1% of the total equity assets in SEC 13F filings, and the largest 10 managers managed 23.4% of these assets.[1] According to some theories, idiosyncratic shocks to the largest individual players are hardly diversifiable (Gabaix, Gopikrishnan, Plerou, and Stanley 2006; Gabaix 2011). In this vein, large institutional investors are not equivalent to a collection of smaller independent entities. Rather, they have an uncompressible institutional identity that leaves a large footprint in the market. That is, they are "granular."

The asset management space has experienced many examples of idiosyncratic events at the institutional investor level that have had widespread repercussions in the financial system. At the peak of the Global Financial Crisis, stocks held by hedge funds that had brokerage relations with Lehman Brothers experienced a drop in liquidity after the bank collapsed (Aragon and Strahan 2012). In early 2012, JP Morgan's trader Bruno Iksil (the "London Whale") built a large short position in credit default swaps that led to trading losses exceeding $6 billion within weeks and distorted market prices of credit-linked securities.[2] Moreover, on August 1, 2012, a glitch in an untested trading program at Knight Capital led to 4 million order executions in 148 stocks within 45 minutes. These orders created losses of $440 million to Knight Capital due to the significant intraday price impact on many stocks.[3] Lastly, the sudden departure of co-founder Bill Gross from Pimco on September 26, 2014 caused unprecedented large withdrawals from the flagship Total

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[1] These numbers are computed using the SEC 13F reports, which only contain equity-like securities. They are, however, consistent with the report by the Office of Financial Research (2013), which calculates that as of December 2012 the largest asset manager (Blackrock) oversaw 7.2% of the total assets under management (AUM) in the United States, and the largest 10 and 20 managers managed 35.2% and 49.4%, respectively.

[2] See Ruhle, Stephanie, Bradley Keoun, Mary Childs, 2012, JP Morgan Trader's Positions Said to Distort Credit Indexes, Bloomberg Business http://www.bloomberg.com/news/articles/2012-04-05/jpmorgan-trader-iksil-s-heft-is-said-to-distort-credit-indexes. Zuckerman, Gregory, and Katy Burne, 2012, London Whale Rattles Debt Market, Wall Street Journal http://www.wsj.com/articles/SB10001424052702303299604577326031119412436. Hurtado, Patricia, 2015, The London Whale, Bloomberg QuickTake http://www.bloombergview.com/quicktake/the-london-whale.

[3] Securities and Exchange Commission, Order Instituting Administrative and Cease-to-Desist Proceedings (Knight Capital Americas LLC), October 16, 2013 https://www.sec.gov/litigation/admin/2013/34-70694.pdf.

Return Fund. To come up with the cash, Pimco engaged in drastic liquidations of its holdings.[4,5] It is important to note that idiosyncratic events need not be rare or extreme to have an impact on asset prices. A large institution that initiates trades to accommodate investor flows or for portfolio rebalancing or for risk-management reasons may cause price dislocations.

Regulators have expressed concerns about systemic risks that could result from the high concentration of assets under a single large manager: "The failure of a large asset management firm could be a source of risk, depending on its size, complexity, and the interaction among its various investment management strategies and activities" (Office of Financial Research 2013). The Financial Stability Board (FSB 2013) has voiced additional concerns about whether non-bank, non-insurance financial institutions are systemically important or "too-big-to-fail." Furthermore, a recent FSB directive (2015), focusing on systemic risks originating from non-bank, non-insurer institutions, voiced the concern that while research studying market contagion is abundant, there is a lacuna in the research about individual organizations.[6]

Given that the evidence on the effect of large firms is so far anecdotal, the purpose of this paper is to provide a large-sample study on the impact of large institutional investors on price stability. Using more than 35 years of ownership data from 13F filings, we measure the effect of large institutional ownership on stock volatility. Our results show that the presence of large

[4] See Ablan, Jennifer, 2014, "Bill Gross Effect" Sparks Flows into BlackRock, Legg Mason: KBW, Reuters http://www.reuters.com/article/2014/10/08/us-pimco-allianz-gross-idUSKCN0HX1Y820141008, Goldstein, Matthew, 2014, Bill Gross, King of Bonds, Abruptly Leaves Mutual Fund Giant Pimco, New York Times Dealbook http://dealbook.nytimes.com/2014/09/26/william-gross-leaves-pimco-to-join-janus/, and Mackenzie, Michael, and Gregory Meyer, 2014, Gross Triggers Sell-Off in Interest Rate Derivative Positions, Financial Times, October 5, 2014. Grind, Kirsten, and Gregory Zuckerman, 2014, Amid Crisis Pimco Steadies Itself, The Wall Street Journal, December 15, 2014 http://www.wsj.com/articles/amid-crisis-caused-by-bill-grosss-exit-pimco-steadies-itself-1418614371. This anecdotal evidence illustrates the magnitude of the sell-off and the threat of a liquidity crunch that Pimco faced in the months following Gross' departure, as well as the ensuing price drops that spread to many securities in Pimco's portfolio. In the immediate aftermath, the performance ranking of Pimco's Total Return Fund dropped to the 23rd percentile, before rebounding to the 99th percentile after price reversals on the bonds with the most price pressures when Pimco's outflows steadied in the following months.

[5] In spite of these adverse developments, some argue that Pimco was able to avoid a large-scale fire sale through holding the fund's clearance in-house. For example, in its response to the Secretariat of the Financial Stability Board, Blackrock Inc. used Bill Gross' departure as an example of a large-firm idiosyncratic event that did not cause havoc in financial markets (http://www.blackrock.com/corporate/en-gb/literature/publication/2nd-nbni-gsifi-fsb-iosco-052915.pdf.). See also Weiss, Miles, 2015, Pimco May Have Averted Fire Sale After Gross's Exit http://www.bloomberg.com/news/articles/2015-06-11/pimco-may-have-averted-fire-sale-after-gross-s-exit.

[6] Some of the largest U.S. funds responded to the FSB's allegations that they are systemically important. Fidelity, for example, claimed that the FSB's approach is "irredeemably flawed" and its claims "would be counterproductive and destructive." See Jopson, Barney, 2015, Top US Fund Managers Attack Regulators, Financial Times, May 31, 2015, http://www.ft.com/intl/cms/s/0/6fbde67a-061b-11e5-89c1-00144feabdc0.html.

institutions leads to more volatile stock prices. Importantly, the effect that we identify constitutes a separate layer of price volatility from the fragility induced by common institutional owners with correlated flows (Greenwood and Thesmar 2011). It follows uniquely from ownership by large institutions.

We use two distinct identification strategies to address potential endogeneity concerns (e.g., the fact that large institutions may prefer stocks with higher volatility). The first relies on "local bias," that is, the prior finding that asset managers overweight firms that are located closer to the investor's headquarters (Coval and Moskowitz 1999). We use an indicator for whether a company is headquartered in the same state as the large asset managers (Baik, Kang, and Kim 2010). Consistent with a local bias, we show that institutional investors hold significantly larger stakes in firms that are located in the same state. This variable is a valid instrument because it is not likely to have a direct effect on stock volatility. The second stage in the analysis shows that instrumented ownership by large institutions leads to significantly higher stock volatility. Using this identification technique, we find that the economic magnitude is large: a 1 % increase in stock ownership causes an increase in stock volatility of about 12 to 18 basis points, relative to a daily average of 3.5%. The caveat is that these estimates possibly measure a local average treatment effect (LATE) (Imbens and Angrist 1994), that is, the impact of ownership on stocks that enter the institutional portfolio only because of their geographical location, which are likely to be small and illiquid. For this reason, we interpret the instrumental variable estimates as an upper bound for the effect of interest.

Our second identification strategy relies on the merger between two large institutional investors—Blackrock and Barclays Global Investors (BGI)—that took place at the end of 2009 and spawned the top institution in the market. The granularity theory in this context suggests that the shocks to one large consolidated organization (the merged firm) have a greater impact than the shocks to separate entities (the pre-merger organizations). Consistent with this hypothesis, we find that stocks owned by the combined entity exhibit higher volatility than stocks owned by the pre-merger firms and that this effect persists well after the merger event. As the merger event is arguably exogenous relative to the portfolio stocks' characteristics (including volatility), we can interpret the effect on volatility as the causal effect of ownership by the joint entity.

The study delves deeper into the origin of these effects and the channels through which they play out. First, we explore the role of large institutions' trades in increasing stock volatility. For this, we draw inspiration from Gabaix, Gopikrishnan, Plerou, and Stanley's (2006) theoretical prediction that large institutions affect stock prices through their trading activity. Using trade-level data from ANcerno, we find that the trades by top institutions are associated with larger price impact than those of smaller institutions. When we account for the concave relation between price impact and trade size, the incremental price impact of large firms is no longer significant. While we are aware of the potential endogeneity in the estimation of the price impact of order flow, we take these results as suggestive that a potential channel for the impact of top institutions on volatility is the price pressure generated by their large trades.

The question remains, however, whether large institutions' trades are different from those of a collection of small investors that add up to the same total size. If they are not, then unbundling a large institution into smaller pieces would not eliminate the potential price distortions induced by large institutions. To address this question, we compare the trades of large institutions to those of a random set of smaller independent institutions with the same total amount of portfolio holdings. The goal is to build a synthetic institution representing the counterfactual world in which large institutions are broken up into smaller entities. Granularity theory suggests that while small institutional investors may suffer idiosyncratic shocks, their trades will cancel out one another. In contrast, idiosyncratic shocks to a large institutional investor will translate into large trades, which can have a bigger impact on prices. The underlying assumption is that the different divisions within a large firm may trade in a correlated way if, for example, fund managers use the same source of security research, if there is a centralized risk-management function, or, more generally, if there is an investment philosophy that characterizes the whole institution.

Our results show that large investors trade in a more concentrated portfolio of stocks and in bigger sizes than the synthetic institutions. For example, after 2000, the 10 largest firms trade in just 51.3% of the available stocks, while the synthetic organizations trade in 71.5% of the universe. Furthermore, the size of the trades of the large investors is substantially bigger than that of the synthetic institutions and therefore are more likely to impact prices. For example, 16.2% of the trades of large institutional investors are above the 90th percentile of the distribution of trades of the synthetic institutions, and 3.7% of the trades of the large firms exceed the 99th percentile of the same distribution. While the distance has shrunk over time, the ranking persists through the end of the sample in 2015.

Finally, we explore the role of investor flows into large asset managers as potentially one of the causes for the large trades we document. We execute this test using a monthly mutual fund dataset, because fund flows are measured more accurately and on a relatively higher frequency. We document that the correlation between mutual fund flows is higher among funds under the same management company than among independent funds by approximately 10% of one standard deviation of the correlation coefficient. Thus, correlated investor flows could be one of the reasons that large institutional investors are forced to place large trades.

We close the study by exploring the nature of the increase in stock volatility. It may be the case that the increase in volatility is a desirable outcome of institutional ownership, if, for example, large institutions encourage information production and faster price discovery. We test whether large institutions contribute to or detract from market efficiency in two ways. First, we document that ownership by large institutions is associated with stronger daily return autocorrelation, indicating reduced price efficiency. Second, we show that the returns of stocks that are owned by large institutional investors co-move with the returns of the rest of these institutions' portfolios, controlling for the effect of standard factors. This evidence suggests that the underlying securities are exposed to the same shocks, presumably spilling over from the large institutional investor. The effect becomes larger as institution size increases. This finding, therefore, extends prior evidence on abnormal co-movement in institutional portfolios (Greenwood and Thesmar 2011, Anton and Polk 2014) by showing that the size of the institutional investors also matters in determining co-movement.

Overall, our study shows that ownership by large institutional investors increases the volatility in the prices of the portfolio securities. Our analysis shows that institutions cause the increase in volatility through large trades, which translate into substantial price pressure. Large institutions have a "granular" nature that leads them to trade in a less diversified way than a random collection of independent entities. Finally, our analysis suggests that the increase in volatility is associated, at least in part, with an increase in noise.

The idea that idiosyncratic shocks to large firms are granular and cannot be diversified away is first explored by Gabaix (2011) with an explicit, but non-exclusive, reference to economic growth. The idea is applied to the context of financial markets by Gabaix, Gopikrishnan, Plerou, and Stanley (2006). These authors develop a simple model relating the statistical distribution of return volatility to the fat-tailed distribution of institutional investors' assets under management. Sias (1996) and Bushee and Noe (2000) find further evidence that increases in institutional ownership are accompanied by a rise in stock volatility, without an explicit focus on large firms. 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 reduced-form evidence on the effect of the ownership structure (large vs. other investors) on stock-level volatility.

The granularity idea appears in other contexts as well. 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 of 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. Siriwardane (2015) shows that the credit default swap (CDS) market is very concentrated (very few sellers) and that prices of CDS contracts are affected by the capital constraints of these sellers.

Beyond applying the granularity theory to the institutional investment space, this paper contributes to the literature on the effect of institutions on asset prices, risk spillovers, and financial stability. A substantial body of work shows the impact of institutional trades on asset prices, including Shleifer (1986); Brady (1988); Jones and Lipson (2001); Corsetti, Pesenti, and Roubini (2002); Coyne and Witter (2002); Werner (2003); Chiyachantana, Jain, Jiang, and Wood (2004); Barberis, Shleifer, and Wurgler (2005); Greenwood (2005); Coval and Stafford (2007); and Wurgler (2011). Moreover, other papers establish that institutions can affect the volatility and correlation of asset returns (Greenwood and Thesmar 2011, Jotikasthira, Lundblad, and Ramadorai 2012, Lou 2012, Anton and Polk 2014, Chang, Hong, and Liskovich 2015, Bartram, Griffin, Lim, and Ng 2015) or develop intermediary asset pricing models (Adrian, Moench, and Shin 2010, He and Krishnamurthy 2012, Adrian, Moench, and Shin 2013, and Muir 2014). In addition, Basak and Pavlova (2013a, 2013b) show theoretically that an asset included in an index tracked by institutional investors increases the non-fundamental volatility in that asset's prices. Ben-David, Franzoni, and Moussawi (2015) provide empirical evidence that ETFs increase stock volatility.

Allen and Gale (2000) and Boyson, Stahel, and Stulz (2010), among others, show that shocks within one part of the financial system may propagate throughout the rest of the system, causing a large-scale stress event. A recent paper by Massa, Schumacher, and Wang (2016) studies the impact of the Blackrock-BGI merger on the behavior of other institutional investors. They find evidence that other institutional investors migrated away from stocks with large ownership by the combined entity *before the merger*, consistent with fears of destabilizing trades by the merged entity. Our evidence complements theirs in showing that *after the merger*, ownership by the combined entity is indeed destabilizing for prices.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents the main evidence of the effect of large institutional ownership on stock volatility. Section 4 examines the channels by which risk may transfer from large institutions to stocks, and Section 5 investigates the nature of the volatility increase. Section 6 concludes.

2 Data Description

We construct our sample of asset managers using institutional ownership data from the first quarter of 1980 until the third quarter of 2015 that was compiled by Thomson-Reuters from U.S. Securities and Exchange Commission (SEC) 13F filings.[7] The 13F filings require all institutions with investment discretion over $100 million or more of 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.[8,9]

[7] See Ben-David, Franzoni, and Moussawi (2012) for institutional details regarding 13F data and an overview of the Thomson-Reuters Institutional Ownership database.

[8] On a quarterly basis, the SEC publishes the official list of Section 13F securities at https://www.sec.gov/divisions/investment/13flists.htm. The list contains mainly equity and equity-like securities such as publicly traded common stocks, convertible bonds, ETFs, and options on equity securities.

[9] Asset managers also report positions that are managed for clients. For example, consider CalPERS, which uses Blackrock as one of its asset managers. According to CalPERS' investment statement (https://www.calpers.ca.gov/docs/forms-publications/facts-at-a-glance.pdf), it has about $160 billion in public equity, 82% of which is managed internally (http://www.pionline.com/article/20150909/ONLINE/150909854/calpers-to-consider-taking-activist-manager-portfolio-in-house). Because its 13F assets as of the end of June 2015 account for only about $67 billion (http://www.sec.gov/Archives/edgar/data/919079/000114036115032277/xslForm13F_X01/primary_doc.xml), CalPERS is likely to have a few billion dollars reported by asset managers like Blackrock and others. Those assets will be reported under the respective asset managers' 13Fs (for advising and executing on investment decisions).

We examine the largest asset management firms in each quarter based on a rolling four-quarter average of the rankings of their aggregate equity holdings, as disclosed in institutional 13F filings. In our tests, we include all stocks in the CRSP universe, regardless of whether they are held by the largest asset managers. We use data from CRSP and Compustat to construct other stock-level variables. Given that the main variables from the 13F filings are at a quarterly frequency, we construct all other variables at a quarterly frequency. We also use trade-level data, compiled from ANcerno. We describe this data in section 4.1.

The variables of interest are the *Ownership* of each stock by the largest institutional investors. The main dependent variable that captures firm risk is *Daily volatility (%)*, which is measured for each stock in each quarter as the standard deviation of daily log returns. Panel A of Table 1 provides summary statistics for our sample of stocks. The mean *Daily volatility* over the entire sample is 3.5%, and the median *Daily volatility* is 2.8%. Moreover, we observe that for the average stock in our sample, 37.1% of its shares are owned by institutional investors (*Ownership by all institutions)*. We also provide some sample statistics specific to the Blackrock-BGI merger we study (Section 3.4.2) and to our mutual fund flows analysis (Section 4.3). During this merger period, the average stock's *Daily volatility* is 3.0%, which is close to the mean of our overall sample. Appendix A provides a detailed description of the variables that we use in the study.

We measure large institutional ownership at several levels: the ownership by each of the largest institutions (top 1 to top 10) and the aggregated ownership by subsets of large institutions, specifically the top 3, top 5, top 7, and top 10 institutions. Table 1, Panel B provides summary statistics for our sample of asset managers. The largest institutional investor (top 1) holds 1.8% of the outstanding shares of the average stock in our sample with a standard deviation of ownership of 2.6%. Average holdings follow a nearly monotonic decrease from the largest to the 10^{th}-largest institution.[10] As a group, the largest three institutions hold a combined 3.9% of the average stock in our sample, while the aggregate ownership of the top ten institutions is on average 7.6%. 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.

[10] Because we report averages across different stocks and quarters, it does not have to be the case that these averages are monotonically decreasing in the institutional ranking. As said, the institutional rank is constructed based on the overall stock ownership over four quarters, on a rolling basis.

We also provide summary statistics for other key variables (Table 1, Panel B). *Same state* is a dummy that captures whether a firm's headquarters is in the same state as the headquarters of the institutional investor, which we use to construct an instrumental variable for some of our analysis. *Beta with top institutions* estimates the sensitivity of the firm's daily returns to the returns of the rest of the portfolio of the top institutional investors.

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 the average stock is increasing over time. For example, the largest institution in the economy quadruples its holdings from 1.4% of the equity market at the beginning of the sample (1980) to 5.4% at the end of the sample (2015). Similarly, the largest ten institutions own 5.6% at the beginning of the sample and 22.3% at the end. Over the same period, ownership by all institutions roughly doubled. Comparing this trend to the faster growth of large institutions, suggests that ownership has become more concentrated over time.

Table 1, Panel C provides summary statistics for the ownership by asset managers, calculated by index. We observe that the largest institutions hold a greater proportion of the largest stocks, defined by the stocks' inclusion in the S&P 500. While the largest institution holds an unconditional average of 1.7% of the shares outstanding of all companies in our sample, it holds 2.9% of the shares outstanding of the S&P 500 members and 2.7% of the shares of the Russell 1000 members. This pattern persists for all institutions in the top ten.

Table 1, Panel D provides a correlation matrix for the key variables used in our analyses. Most variables exhibit low correlation with each other, but there are some exceptions. Ownership by the top ten institutions is correlated with the ownership by all institutions at 78%. Moreover, the ownership by the top 10 institutions is correlated at 53% with Greenwood and Thesmar's (2011) measure of fragility, which captures the concentration of institutional ownership of a stock, weighted by the volatility and correlation of the trading needs of its investors. Despite this high correlation, we find in later analyses that ownership by large institutions has independent explanatory power for volatility, even when fragility is included in our regressions.

Finally, Appendix B reports statistics on the large investment firms that make up our sample. We compute the length of time that each firm stays in our sample, its average long equity holdings, its average quarterly turnover, and the average rank of the firm while in the sample. The firm with the highest average ranking stays in our sample from the third quarter of 2010 until the third quarter of 2015. This large institution had average equity assets of $1.04 billion and a quarterly turnover of 3.55%. Overall, our sample contains 40unique institutions that fell within the top ten institutions at some point during our sample period. They hold an average of $172 billion (inflation adjusted to the end of 2015) in assets in a given quarter of our sample.

3 The Effect of Large Institutions on Stock Volatility

We begin our analysis by using ordinary least squares (OLS) regressions to explore the relation between ownership by large institutional investors and stock-level volatility. We lag ownership by one quarter to reduce the concern that it is endogenous with respect to volatility. For the same reason, in some specifications we control for lagged volatility or, alternatively, for stock fixed effects. We address the remaining endogeneity concerns in Section 3.4 through an instrumental variable approach as well as a natural experiment.

3.1 Base Regressions

Our main OLS specification takes the following form:

$$Volatility_{iq} = TopInstOwnership_{i,q-1} + Controls_{i,q-1} + Time\ FE_q + Stock\ FE_i + \varepsilon_{iq} \quad (1)$$

The sample frequency is quarterly, and variables are measured at the stock level. The dependent variable is the stock's daily return volatility measured over the calendar quarter. 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 *volatility* (when stock fixed effects are not included), lagged *log(market cap)*, lagged *book-to-market* ratio, *past 6-month returns*, lagged inverse price ratio (*1/price*), lagged *Amihud illiquidity* measure (Amihud 2002), and lagged *total ownership by all institutions*. We also add in a variable that measures the lagged total *ownership by bottom institutions* whose aggregate equity holdings sum up to that of the largest ten institutions. This variable can serve as a placebo test to verify whether the effect of interest originates from the size of assets under management, irrespective of whether they are managed by top institutions. Lastly, our specifications include calendar quarter fixed effects and, in some cases, stock 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, Panels A and B. Panel A does not include stock fixed effects, while Panel B does. We note that up to the 30th largest institution, the positive relation between ownership by large institutions and stock volatility is statistically significant. Column 4 of Panel B shows that a 1% increase in the top 10 institutions' stock ownership coincides with a 0.82 basis point increase in daily stock volatility. The economic magnitude of these OLS estimates is therefore not large. Beyond the 20th largest institution, the magnitude decreases by 51% for institutional investors ranked 21 to 30, and it is indistinguishable from zero for institutional investors ranked 31 to 50. Furthermore, the effect of ownership by the bottom institutional investors with the same total size as the top ten institutions is not statistically different from zero, suggesting that the size of assets under management is not relevant in itself, if the assets are not under the same institutional umbrella. We explore this issue further in Section 4.2.

To explore whether these effects are relegated to small and illiquid stocks, we focus on the subsample of S&P 500 firms in Table 2, Panel C. The results again show that the holdings by the top ten institutions are associated with higher stock-level volatility. The effect is more concentrated, though, as ownership by institutions 11 to 20 is not significantly associated with a change in stock volatility, and institutions 21 to 50 are associated with lower volatility. We conclude that the relation between ownership by large investors and stock-level volatility is not merely a small-stock phenomenon.

3.2 The Effect during Financial Crises

Financial crises are of particular interest, because asset managers often face withdrawals by their investors and therefore may engage in liquidations and rebalancing. For example, Ben-David, Franzoni, and Moussawi (2012) show that hedge funds engaged in massive liquidations of their equity positions during the 2008-2009 financial crisis as a response to capital outflows. The effects that we identify are therefore potentially larger in crisis periods.

To test whether the effect of interest is stronger during crisis periods, we limit our sample to the quarters that are defined as financial or banking crises in Berger and Bouwman (2012).[11] Table 2, Panel D presents the results of this analysis. The first four columns show the relation between holdings of the top 3, 5, 7, and 10 institutions and stock volatility, respectively. Columns (5) to (8) use a sample that is restricted to the eight quarters in the 2008–2009 crisis period.

Relative to the estimates for the entire sample, we note that the association between ownership by large institutions and stock volatility is higher during crises and especially higher during the financial crisis of 2008-2009. For the whole set of crises, the slope on ownership by the top 3 institutions in Panel D is 15% larger than the coefficient in Panel B. During the 2008-2009 period, the same slope is 150% larger. In Panel E, we show that the effect of large institutional ownership on volatility remains significant outside of the crisis periods and that the coefficients are slightly smaller than those in Panel D. For example, the slope for ownership by the top 3 institutions is 0.609, with a t-statistic of 3.30.

In sum, we find that the effect of interest is larger in periods of market stress, while it also remains significant also in non-crisis times. This result is in line with Gabaix, Gopikrishnan, Plerou, and Stanley's (2006) prediction that the impact of large institutions on stock prices is especially significant in a relatively illiquid market. Koijen and Yogo (2015), instead, estimate a general equilibrium model and show that the trades of large institutions were responsible for only a small fraction of *aggregate market* volatility during 2008-2009 financial crisis. Our focus and our approach are different, however. We estimate a reduced-form specification showing that, *in the cross section of stocks*, the effect of large institutions on stock-level volatility is comparatively more important than the effect of other institutional investors.

3.3 Greenwood and Thesmar (2011)'s Fragility Measure

We also modify our base analysis by including the measure of stock fragility (G) from Greenwood and Thesmar (2011). Their fragility measure captures the concentration of institutional

[11] These periods are the stock market crash in the fourth quarter of 1987; the credit crunch from the first quarter of 1990 until the fourth quarter of 1992; the Russian debt and long-term capital management (LTCM) crisis in the third and fourth quarters of 1998; the dot-com bubble and the September 11 crisis, from the second quarter of 2000 until the third quarter of 2002; and the subprime lending crisis from the third quarter of 2007 until the fourth quarter of 2009.

ownership in a stock, weighted by the volatility and correlation of the trading needs of its investors. These authors find a significantly positive link between fragility and volatility. While there may be overlap between the concentration of institutional ownership in a stock and ownership by large institutions, as suggested by the correlations in Panel D of Table 1, the two concepts are clearly distinct. In particular, high fragility can result from high institutional portfolio concentration, but these institutions do not necessarily have to be the largest ones. On the other hand, large institutions may hold a large fraction of the shares of a company, while their portfolios are well diversified, hence not concentrated in the specific stock, which leads to a low fragility score. Overall, our focus is ownership by large institutions, irrespective of whether these firms' portfolios are concentrated or not and of whether the flows into these portfolios are correlated across institutions.

To test for an independent effect of ownership by large institutions, we include Greenwood and Thesmar's (2011) measure of fragility in our main regression model. Table 2, Panel F, presents the results of this analysis. We again find that the coefficient on large institutional ownership is positive and statistically significant. Meanwhile, the coefficient on Greenwood and Thesmar's fragility measure is also positive and statistically significant, with coefficients that are similar in magnitude to those found in the original study. Going forward, we restrict our usage of the fragility measure because the data required to construct this variable deplete our sample size by nearly 20%. In order to have the largest sample possible and to draw reliable conclusions, we include this variable only in some robustness checks.

3.4 Identification

Stock ownership by large institutional investors may be endogenous with respect to volatility. In such a case, the association between large institutional investors and volatility may not reflect a causal relation. For example, one possible explanation for this correlation is that large institutional investors might prefer holding popular stocks, which exhibit large trading volume and volatility. More likely, large institutional investors may prefer large liquid stocks, which are less volatile. This conjecture finds support in the summary statistics in Table 1, Panel C, which show a larger presence of top institutions in bigger stocks. In such a case, the OLS coefficients would be downward biased.

To identify a causal relation in which ownership by large institutional investors leads to an increase in stock volatility, we provide evidence from two distinct identification strategies. We first use an instrumental variable approach exploiting the finding in prior studies that institutional investors have a local bias and therefore have greater holdings in firms that are headquartered nearby (Coval and Moskowitz 1999, and Baik, Kang, and Kim 2010).[12] Our second identification strategy relies on the merger of two large institutions (Blackrock and BGI) at the end of 2009, which led to the creation of an even larger entity.

3.4.1 Identification Strategy I: Local Bias

In our first identification strategy, we exploit the local bias of institutional investors. Coval and Moskowitz (1999) show that mutual funds overweight firms that are located closer to their headquarters. Moreover, firms targeted by mutual funds tend to be of higher quality (Coval and Moskowitz 2001). Confirming the local bias, Giannetti and Laeven (2015) find that during times of crisis, institutions are more likely to sell stocks of firms that are located far away. In particular, we follow Baik, Kang, and Kim (2010), who document that institutional investors hold larger stakes in firms that are headquartered in the same state. Large investors may tend to hold greater stakes in firms from the same state for several reasons. For example, it is possible that the clients of the institutional investors prefer local firms (e.g., due to political reasons). Other reasons could involve informational advantages, or governance and legal issues. Irrespective of the motivation for the local bias, the common location of the top institution and the company's headquarters seems unlikely to have an independent relation with stock volatility, especially in light of the fact that our top institutions are not concentrated in a specific area of the country (see Appendix B). Hence, we are confident that the exclusion restriction is valid, that is, the identifying assumption that the only channel through which same-state location with a large institution correlates with stock volatility is through the ownership of the stock by the large institution.

We use a two-stage least squares (2SLS) framework for our tests. The potentially endogenous regressor is the aggregate ownership by the top institutions. For each of these institutions, we construct an indicator for whether the institution and the firm are headquartered in

[12] Local bias is a pervasive feature of retail investors' portfolios as well. See, e.g., Grinblatt and Keloharju (2001), Huberman (2001), and Ivkovic and Weisbenner (2005).

the same state. Then, our instrument is the sum of this indicator across the top institutions that we consider in a given specification (we label it "Same state score"). Therefore, the instrument ranges between 0 and the number of top institutions that are included in the test. Except for the case of the top 3 institutions, never in our sample are all of the top managers headquartered in the same state.

In the first stage, we regress ownership by top institutions in stock i in quarter q on the instrument and controls, including time fixed effects:

$$TopInstOwnership_{iq} = Same\ State\ Score_{i,q} + Controls_{i,q-1} + Time\ FE_q + \varepsilon_{iq} \quad (2)$$

The estimates of Equation (2) are reported in Table 3, Panel A. The coefficient on the instrument shows that, consistent with a local bias, institutional investors hold larger stakes in firms that are headquartered in the same state. The instrument is statistically significant with t-statistics ranging from 3.6 to 4.8. At the bottom of the table, we also report the p-values for the Angrist and Pischke's (2009) F-test for the null hypothesis of a weak instrument. In all specifications, we are able to reject the null at the 1% level.[13]

The exclusion restriction in this instrumental variables setup is that same-state residency affects stock volatility only through the ownership by top institutional investors. One violation of this restriction is the possibility that large institutional investors are encouraged or requested (e.g., through moral suasion by political powers) to hold local firms in financial distress in order to provide some price support. Similarly, they could act of out "local patriotism." In this narrative, the distressed firms would also have higher volatility. To control for this possibility, we include two types of controls. First, we include firm-level measures of financial distress: F-score (Piotroski 2000), O-score (Ohlson 1980), Z-score (Altman 1968), CHS distress risk (Campbell, Hilscher, and Szilagyi 2008), and the fraction of quarters with negative income over the previous two years. As reflected in the first stage in Table 3, Panel A, large institutional investors are more likely to hold

[13] We also use an F-statistic, with degrees of freedom adjusted for clustering as in Kleibergen and Paap (2006), to test whether the instrument is weak. Staiger and Stock's (1997) rule of thumb is that instruments with F-statistic values below 10 are considered weak. The F-statistics range from 11.4 to 22.3; hence, all specifications pass the rule-of-thumb test. More formally, Stock and Yogo (2005) provide critical values for a weak instrument test based on maximum size distortion, using the same F-statistic. In the case of one endogenous regressor and one instrument, the critical values are 16.38, 8.96, 6.66, and 5.53, for maximum acceptable rejection rates of the null hypothesis of irrelevant instruments of 10%, 15%, 20%, and 25%, respectively. According to this test, in Columns (1) and (2), there may be a suspicion of weak instruments, but in Columns (3) and (4), we are able to reject the null hypothesis at all critical values.

successful firms than firms in financial distress. Second, we include annual GDP growth of the state of residence of the company issuing the stock, as well as two quarterly lags of the same variable. The regression shows that state-level economic conditions do not affect the behavior of top institutional investors.

The second stage is a regression of stock volatility on the predicted holdings of the large institutional investors using the same controls as in the first stage:[14]

$$Volatility_{iq} = IV(TopInstOwnership_{i,q-1}) + Controls_{i,q-1} + Time\ FE_q + \varepsilon_{iq} \quad (3)$$

In all four specifications, the two-stage least-squares coefficient on ownership by the top institutions is statistically significant. Under the assumption of a valid instrument, the coefficients measure the causal impact of ownership by top institutions on stock-level volatility. The IV estimates are larger than the OLS coefficients in Table 2 by almost two orders of magnitude. While the larger IV estimates can in general stem from a weak instrument, this concern does not seem relevant in our context, as we are able to reject the hypothesis of weak instruments. Based on the slope in Column (4) of Panel B, Table 3, we infer that a 1% increase in ownership by the top institutions leads to an increase in daily volatility of about 11 basis points. Considering that average daily volatility is about 3.5%, the effect seems economically important.

The comparison between the OLS and IV estimates suggests a negative bias in the former. This bias can originate from the fact that the large institutions in our sample are sponsors of passive funds and ETFs that are benchmarked to major stock indexes. Index stocks, being larger, are on average less volatile. This channel introduces a negative correlation between ownership by large institutions and stock volatility. By exploiting exogenous variation in ownership induced by the local bias, we are able to filter out this negative correlation.

To be conservative in our inference on the magnitude of the effect of interest, we should allow for the possibility that the IV estimates measure a local average treatment effect (LATE, Imbens and Angrist 1994). Specifically, the estimated coefficient represents the average effect of an increase in top institutional ownership on the stocks that are held only because they are in the same state as the top institutions. These firms would not otherwise appear on the managers' radar

[14] The two-stage least-square estimates are obtained using Stata's ivreg2 command. Therefore, the standard errors are adjusted to take into account the generated regressor from the first stage. Also, as in the rest of our analysis, we cluster standard errors at the stock level.

screens. Hence, they are likely to be small stocks, for which the effect of interest is larger due to their illiquidity. If this argument is correct, the IV coefficients represent an upper bound for the effect of interest.

Finally, Table 3, Panel C, shows the second stage of an IV regression that includes Greenwood and Thesmar's (2011) measure of fragility. The coefficient on our measure of stock ownership by large institutions again is positive and statistically significant in all specifications.

3.4.2 Identification Strategy II: Evidence from the 2009 Blackrock-BGI Merger

Another way to test the idea that large institutional investors increase volatility is to compare the relation between institutional ownership and stock-level volatility before and after a major merger of institutional investors. If the size of the institutional investors affects the volatility of the stocks in their portfolios, holdings by the combined institution resulting from the merger should have a larger impact on volatility than holdings by the two separate institutions before the merger. 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.

If the large size of institutional investors is the cause of higher stock volatility, then breaking up large institutions into smaller units may lead to lower noise in stock prices. The analysis of this policy implication may be of particular interest to regulators. While a break-up of a large institution into smaller units is not present in our sample period, the causal interpretation of the merger event allows us to reverse the logic and address regulators' question.

We focus on the merger between two large institutional investors in December 2009. In the quarter preceding the merger, BGI held equities worth about $596 billion (Top 1) and Blackrock held equities worth about $156 billion (Top 12). In December 2009, the combined entity was the largest institutional investor in the equity market, overseeing approximately $815 billion worth of equities. The merger caused the largest institutional investor to increase its asset holdings by 37% overnight.

Our specification resembles a difference-in-differences approach because we examine the effect on volatility of the combined stock-level ownership by the two institutions before and after the merger; after the merger, ownership is measured for the resulting institution. The main distinction from a difference-in-differences analysis is that we focus on the effect of a continuous variable (ownership by the merging institutions), as opposed to having treatment and control groups.

An important question relates to the exogeneity of the merger with respect to the outcome variable of interest, that is, stock volatility. In particular, if the motivation behind the merger relates to the stock volatility, it is possible that the effects that we observe might be biased and do not reflect the increase in the size of the institutional investor. To address this concern, we rely on the investigative work of Azar, Schmalz, and Tecu (2015) regarding the drivers of the merger. They report that the merger took place following the desire of Barclays to sell some of its divisions in order to strengthen its balance sheet following the financial crisis. Blackrock made a bid of $13.5 billion. The merger was announced on June 11, 2009, and was completed at the end of 2009. Hence, it appears that the reason for the merger was unrelated to the volatility of the underlying securities (in support of this claim, also see Massa, Schumacher, and Wang 2016).

We use the following empirical specification. The pre-merger window is set to last one quarter before the merger completion (2009/Q4) to minimize the confounding effect of the financial crisis of 2008-2009. We look at various post-event windows, from one quarter to eight quarters, after the merger event. We estimate the following specification:

$$Volatility_{iq} = CombinedOwnership_{i,q-1} \times PostMerger + CombinedOwnership_{i,q-1} + Controls_{i,q-1} + Time\ FE_q + Stock\ FE_i + \varepsilon_{iq}, \quad (4)$$

where *Combined Ownership* is the combined holdings of the merging firms in each stock-quarter before the merger, and the ownership of the resulting entity after the merger. The *Post-Merger dummy* is an indicator of whether the quarter is the first quarter of 2010 or later. The variable of interest, the interaction between *Combined Ownership* and *Post-Merger dummy*, captures the impact on volatility of ownership by the combined institution following the merger relative to the pre-merger effect of the two separate institutions. We control for the usual stock characteristics (main effects and interactions with the merger indicator).

The results are reported in Table 4. As usual, standard errors are clustered at the stock and quarter level. The samples in Columns (1) through (8) include post-merger periods ranging from one to eight quarters, respectively. The estimates show that the impact of ownership on volatility increases significantly following the merger. The coefficient on the interaction, which ranges from 1.5 to 2.3, can be interpreted as follows: a 1% increase in the ownership of the largest institution leads to an increase in daily volatility of 1.5 to 2.3 basis points for the combined entity (to be assessed against an average daily volatility of 3.0% during the period).[15]

Relative to the IV analysis, the advantage of the merger experiment is that it allows us to compare the same stocks that are held by large institutions before and after an exogenous event (the merger). Hence, the estimates that we obtain are not specific to the stocks that are held merely because of the variation in the instrument. Rather, they give the average effect across all the stocks in the portfolio of the merging institutions. In this sense, the estimates that we obtain from this analysis have a more general interpretation. On the other hand, we see them as a lower bound on the effect of interest, because they capture the effect of large institutional ownership that is solely induced by the merger event.

Finally, the persistence and stability of the effect across specifications allows us to rule out alternative explanations. In particular, there could be a concern that the event of the merger *per se* increases stock volatility, irrespective of the "large-firm" effect that we aim to identify. For example, trading related to portfolio restructuring in the aftermath of the merger could lead to higher turnover and volatility. However, this alternative story would lead to a temporary effect that wears out as we extend the window. The estimates in Table 4, instead, suggest that the effect persists unabated for at least two years after the merger.

4 Exploring the Granularity of Large Institutions

In this section, we delve deeper into the determinants of the effect of large institutional ownership on volatility by testing the predictions of the granularity hypothesis. First, we test whether the effect of interest plays out through the trading activity of large institutions. Second, we test whether the trades of large institutions are more concentrated and larger than the trades of

[15] We note that Massa, Schumacher, and Wang (2016) find that ownership of the combined entity, as measured *before the merger*, is associated with lower stock volatility after the merger occurs. The difference with our research design is that we measure ownership of the combined entity *after the merger* as well. Our motivation is to capture the effect of the behavior of the combined entity after the merger, e.g., the effect of non-diversifiable large trades. In this sense, we measure an ex-post effect, whereas Massa, Schumacher, and Wang measure the ex-ante effect triggered by the repositioning of other traders in anticipation of the risk of fire sales sparked by the merger.

a random collection of smaller institutions with the same total size. Third, we present evidence consistent with the hypothesis that investor flows into mutual funds display a significant family component, which induces a significant correlation in the flows to the different units of the same institution.

4.1 Large Institutions' Trades and Price Impact

For the first set of tests, we draw inspiration from Gabaix, Gopikrishnan, Plerou, and Stanley (2006), who suggest that, due to their larger portfolios, large institutions are likely to place orders that have a bigger price impact. Hence, we look for a relation between the price impact of trading and the volume generated by large investors.

To this purpose, we use trade-level data in ANcerno. The ANcerno data is provided by Abel Noser Solutions Ltd., which is a consulting firm that works with institutional investors to monitor their trading costs. This data set contains trade-level information at the management company level for about 800 different managers. Although only a subset of the 13F institutions are present in ANcerno, according to the literature, the reported trades are representative of the behavior of the broader institutional universe (see e.g. Puckett and Yan 2011, Anand, Irvine, Puckett, and Venkataraman 2012 and 2013).

We link by name the managers in ANcerno to those that file the 13F form and are able to match 332 different management companies over the 1999-2010 period. The restriction on the sample length is dictated by the presence of institutions' names in ANcerno. About 1% of the firms that we match end up among the top 10 institutions (as classified based on 13F data) at least once in the sample period.

We aggregate the trade-level data at the day-stock-side-manager level (where side is either buy or sell). In this sense, we consider as part of a unique order all the trades by a given manager in the same stock, day, and side of the market. Following the literature, we construct a measure of price impact as the percentage difference between the execution price and a pre-trade trade benchmark, specifically, the opening price for the day (see, e.g., Anand, Irvine, Puckett, and Venkataraman 2013). In particular, for a buy trade, the price impact is the difference between the maximum execution price across all trades within an order and the open price, divided by the open price. For a sell trade, we change the sign and use the minimum execution price within an order. From the summary statistics in Panel A of Table 1, we note that on average, price impact is positive with a mean of 22 bps and a median of 11 bps, suggesting that these institutions on average trade impatiently, i.e., they demand liquidity. Trade size is defined as the total number of shares in a given order over the total trading volume in the stock on a given day. The trades in our data account on average for about 1.3% of the total trading volume. Of these trades, 11.1% are executed by the top 10 institutions.

In the first specification of Table 5, we regress price impact on an indicator for whether the trading manager is among the top 10 institutions. We control for the interaction of stock and day fixed effects, so that we can absorb all the stock level characteristics that vary at the daily frequency. Standard errors are double-clustered by stock and date. We find that, on average, the top 10 institutions have bigger price impact by about 6.2 bps when they trade, which is about 4% of one standard deviation of the price impact variable.

To delve deeper into the source of this result, in the second specification, we include the size of the trade. The rationale for this variable is to assess the extent to which the bigger price impact of large institutions originates from the fact that their trading volumes are larger. Indeed, we observe that half of the price impact can be accounted for by trade size.

The literature (e.g. Hasbrouck 1991, Gabaix, Gopikrishnan, Plerou, and Stanley 2006, Garleanu and Pedersen 2013, and Landier, Simon, and Thesmar 2015) finds a concave relation between price impact and trading volume. Accordingly, we include the squared trade size in Column (3). In this specification, we note that the concave relation between trade size and price impact entirely explains the larger price impact of the top institutions. Hence, the combined results from Columns (1) through (3) suggest that top institutions have a larger impact because they trade bigger volumes.[16]

However, this conclusion should be tempered due to the complexity of measuring the dependence of price impact on order flow (Gabaix, Gopikrishnan, Plerou, and Stanley 2006). First, order flow and returns are jointly determined, raising an endogeneity issue for which the literature

[16] Incidentally, the comparison between Columns (2) and (3) reveals that the probability that a trade comes from a top institution (i.e., the indicator for a trade by top institutions) is in a concave relation with trade size. This evidence suggests that, although trading in bigger size, large institutions break up their trades, possibly because they want to reduce price impact.

has not found a definite solution yet. Moreover, we can only observe the realized trading volume, as opposed to the desired trade size, which makes the estimation of the exact functional form elusive. Finally, trading volume is auto-correlated and depends on other investors' trades. Collectively, these issues suggest that the link between trade size and price impact that we estimate cannot be ascribed unambiguously to the observed trades. Nonetheless, with these caveats in mind, the measured association between the trades and price impact of large institutions still points to the importance of trading activity in explaining the volatility effect from the prior section.

In the next sets of regressions, we replicate the analysis, but change the definition of top institutions. We note that up to the top 20 firms, results are analogous to those for the top 10 investors. As firm size decreases, we find instead that large institutions have a negative price impact. This result suggests that firms that are not at the very top trade more patiently and provide liquidity to the rest of the market. Moreover, the finding resonates with the result in Table 2 that ownership by institutions below the top 20 has a weaker link to stock volatility.

Overall, the evidence is consistent with the results in Gabaix, Gopikrishnan, Plerou, and Stanley (2006). These authors develop a theory in which the trading activity of large investors generates a fat-tailed return distribution, which translates into excess volatility. Hence, their work allows us to assert that the price impact results in this section are part of the explanation for the evidence that ownership by large institutions increases volatility.

4.2 Comparing Large Institutions to a Synthetic Counterfactual

Thus far, the evidence suggests that in the existing market configuration, large institutions' trades have a bigger price impact than smaller institutions' trades. From a policy perspective, however, the relevant question is whether moving to a market populated by smaller firms would be beneficial in terms of volatility. To explore this question, one would ideally compare the existing distribution of institutions to a counterfactual world in which large institutions are replaced with many smaller ones, keeping the amount of assets under management constant. One could argue that in this counterfactual world, the overall impact of trades on prices could be the same as in the actual world, because the same amount of institutional assets needs to be managed. The granularity hypothesis, however, holds that when assets are held by a large institution, as opposed to a group of smaller ones, the ensuing trading activity is more correlated across the different sub-entities, thereby affecting prices more.

To test this conjecture, we contrast large institutions' trades in the existing configuration of the market to the trades of small institutions in a synthetic counterfactual world. To construct the synthetic counterfactual, for each stock-quarter, we bootstrap the trades of smaller institutions (below the 10th) and cumulate the bootstrapped trades to obtain the trading activity of a synthetic institution that has total equity holdings of the same amount as a top institution.

In more detail, 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. Each synthetic institution results from pooling together institutions that rank below the 10^{th} institution. These component institutions are randomly drawn without replacement until the dollar value of the equity holdings of the original institution is matched.[17] We construct a synthetic institution similar in size to the original institution to filter out the scale effect originating from the large portfolio. Doing so also allows us to test whether the trades of the different units that compose a large institution are more correlated among them than the trades of separate institutions, which is a prediction of the granularity hypothesis.

This exercise also reflects the dramatic growth in the size of the largest institutional investors over time. In 1980, the size of the equity portfolio of the largest institutional investor equals the aggregate size of about 25 random institutions. In contrast, in 2015, it takes 424 random asset managers to match the size of the top firm.

To be a valid counterfactual, we need to assume that synthetic institutions are similar in all aspects to the original institutions except for the fact that the original institutions are governed by a centralized body. In particular, we need to assume that the type of investors or investor behavior in the synthetic institutions is comparable to what would prevail in the counterfactual world. Furthermore, we assume that the actual trades of the firms that make up the synthetic institutions do not differ in a meaningful way from the trades that the small institutions would carry out in a market with no large institutions. If these assumptions hold, then the actual trades of small institutions can proxy for the trades that they would carry out in the counterfactual world.

[17] We add a fraction of the last institution drawn to make sure that we exactly match the total dollar value of the equity holdings of the random sample to that of the large institution.

For each stock-quarter, a synthetic institution's trade results from the sum of the trades of the component institutions. A quarterly trade for a given institution in a given stock is the change in the number of split-adjusted shares reported in the 13F filings for two consecutive quarters. It can happen that the component institutions' trades are in opposite directions, so that the resulting synthetic trade is close to zero. If granularity is present, we should expect two effects. First, the trades by large institutions should be more concentrated (i.e., restricted to a smaller set of stocks), e.g., because a manager has the capacity to cover only a subset of existing stocks and the number of managers in a firm does not grow proportionally with assets under management. Second, we expect that large institutions place trades that are systematically larger than the trades placed by synthetic institutions, e.g., because the different units within a large institution follow similar investment policies. In comparing the size of trades across institutions, we focus on the absolute value of the trades, because both buys and sells can cause price pressure and increase volatility.

First, we examine the evolution of trade concentration over time in Figure 2. The figure shows the time series of the average fraction of stocks that are traded by the top 10 institutional investors and the average fraction of stocks that are traded by the synthetic institutions (each paired to an original institutional investor among the top 10). Until the mid-1990s, the fraction of stocks traded by original and synthetic institutions is similar. Since the mid-1990s, however, there is a wedge between the two types of organizations. While synthetic organizations trade each quarter up to 83% of stocks, original institutional investors trade a smaller set of stocks, up to 62% of the stocks universe. Hence, trading by large institutional investors is concentrated in fewer stocks than trading by their synthetic counterparts.

Second, to address the relative size of trades by large institutions, we construct a stock-quarter indicator for whether the original institution's trade is above a given percentile of the distribution of the synthetic institutions' trades. For each top-10 institution, Table 6 reports the average across stocks and quarters of this indicator for the 50th, 90th, 95th, and 99th percentiles. If there were no granularity, we should not observe a disproportionate fraction of large institutions' trades above the cutoff. Instead, the panel shows that the distribution of the original institution's trades has fatter tails than the synthetic institutions' trades. 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 99^{th} percentile. All the numbers are larger than the percentages expected if the distributions were the same for the original and synthetic institutions (i.e., we would expect 50% of trades above the 50^{th} percentile, 10% above the 90^{th} percentile, and so on). The evidence is strongly consistent with the conjecture that large institutions trade in a more correlated way than a collection of random institutions of similar size.

To assess the relevance of this result in recent periods, it is important to provide time-series evidence. To this purpose, we average the indicator of relative trade size across top institutions in a given year, and plot the time series in Figure 3. Each solid line in the figure describes the percentage of trades of large institutions that are above a certain cutoff. The dashed lines with colors corresponding to the solid lines indicate the expected value if the distribution of the original institutions' trades were the same as that of the synthetic trades (i.e., if there were no granularity). For example, the red solid line describes the percentage of trades by large institutions that are above the 99^{th} percentile, while the red dashed line marks the 0.01 level. The scale of the graph is logarithmic to improve legibility. As the chart shows, at the beginning of the sample (1980), trades by large institutions are highly granular: 8.6% of large institutions' trades are larger than that the 99^{th} percentile of synthetic institutions. Over time, large institutions reduce their granularity: in 2015, only 35.7% of large institutions' trades are larger than the trades in the 50^{th} percentile of synthetic institutions. Possibly, over time large institutions have learned to internalize their price impact, as suggested by Goncalves-Pinto and Schmidt (2013) and Koijen and Yogo (2015). Yet, if we focus on the extreme percentiles, we still find significant evidence of trade granularity even at the end of the sample.

Overall, we conclude that large institutions focus on a less diversified set of stocks and make larger trades than a collection of smaller institutions of equal total size. This evidence supports the view that large institutions are granular, that is, the different units within a large institution behave in a somewhat similar way. Consequently, it is likely that in a counterfactual world populated by institutions of smaller size, price impact from trading would be smaller.

4.3 Correlated Flows across Funds within a Family

One potential factor that can lead large institutions to execute bigger trades than what a collection of independent institutions would do is the fact that investor flows are more positively correlated across the different units under the same institutional umbrella. This pattern can occur if institutional clients react to events or news unfolding at the overall institutional level, or in other units of the same institution, and not just to the performance of the individual units, consistent with the granularity hypothesis. As an example, Bill Gross' departure as manager of the Total Return Fund at Pimco (mentioned in the introduction) triggered outflows from other funds at Pimco that Gross was not directly managing. Arguably as consequence of these events, five of Pimco's funds appeared in the infamous ranking of the 10 funds with the heaviest customer redemptions in 2014.[18]

We want to test whether the correlation of investor flows across units of a unique institution is higher than across independent institutions. This analysis is difficult to carry out using the quarterly 13F data that we have used so far, because these data do not include investor flows, but only changes in long equity positions.[19] To overcome this empirical hurdle, we turn to mutual fund data. We can test whether the pairwise correlation of flows between funds in the same family (i.e., funds with the same management company) is higher than the correlation between funds in distinct families.

Using the CRSP Mutual Fund Database, we construct mutual fund flows at the monthly frequency for the years 1980–2014. The database does not have an explicit mutual fund family identifier. We start with all 57,645 fund share classes in the CRSP Mutual Fund Database with data after 1980 and attempt to group them into their family categories, using historical management company information in CRSP, after accounting for variations in management company names over the time series. When such information is not available in CRSP, we try to derive the management company information using the historical fund name itself. We end up with 1,692 distinct groups of share classes with common family assignment, which obviously exceeds the number of fund families in the United States and it reflects our conservative approach in family assignment. We then map all these share classes to their respective portfolios. This information is not available in CRSP for most of the period between 1980 and 2008. Hence, we rely on the WRDS MFLinks database that focuses on U.S. equity mutual fund portfolios.

[18] http://www.ft.com/intl/cms/s/0/22b69960-7423-11e4-82a6-00144feabdc0.html#axzz44HY3rqTx.

[19] Although some studies estimate flows as the difference across quarters in return-adjusted equity holdings, these estimates are inaccurate, because they cannot net out the effect of rebalancing across asset classes and changes in short positions.

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 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 249,665,960 observations, on 8,410 different portfolios belonging to 924 family groups in the period between 1980 and 2015. We note that given our conservative approach in family assignment, we are likely classifying some funds as belonging to different families that are actually in the same family. This potential misclassification, however, can only make finding an effect of family membership more difficult in our analysis. The summary statistics for the variables used in this analysis are in Table 1, Panel A. We note that the average pairwise correlation is not high, at about 3%.

We test whether the correlation between mutual fund pairs is higher when funds belong to the same family. We thus regress the correlation coefficient on an indicator variable for whether the pair belongs to the same family dummy. Table 7 presents the results. The different columns correspond to different combinations of fixed effects: from a specification with time fixed effects (Column (1)) to a specification that includes fixed effects for each fund i-year and fund j-year (Column (4)). 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. We find that the correlation coefficient is about 3.3% 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 higher than that of the entire population of funds. Hence, the effect is economically significant.[20]

Overall, we find supportive evidence for one of the potential channels that make the different units within a large institution behave in a similar way. Investor flows that involve funds within the same family are more correlated. Hence, units within the same institutional umbrella

[20] Given that the large number of observations may raise concerns about the validity of our inference, we have also drawn a random sample of 1% of the observations. The estimates in this restricted sample are very similar to those in the whole sample and statistical significance is also strong.

are more likely to trade in a correlated fashion and, therefore, to have more price impact when adjusting their portfolios in response to flows.

5 The Nature of the Increase in Volatility

After showing that large institutional investors cause higher volatility in stocks, we next explore the nature of the increase in volatility. Higher volatility could reflect greater informational content in returns, which is a desirable effect, or it could indicate that stock returns are noisier, which is an undesirable consequence of large institutions' ownership. We provide two sets of results showing higher ownership by large institutions correlates with a greater amount of noise in stock prices. First, we show that the autocorrelation of returns is more negative and higher in absolute value for stocks that are held by large institutional investors. Second, we present evidence that stocks with higher common ownership by large institutions display a greater amount of abnormal co-movement.

5.1 Daily Return Autocorrelation

The first test looks at the relation between daily return autocorrelation and ownership by large institutional investors. In an efficient market, returns should be unpredictable. Hence, the autocorrelation of returns should be zero under the null hypothesis of efficient markets. Thus, finding that autocorrelation is related to the ownership of large institutional investors supports the view that the increase in volatility that we identify corresponds to a decline in price efficiency.

Our test follows the specification in Equation (1). However, instead of using volatility as the dependent variable, we compute a measure of return autocorrelation. Specifically, we use DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers 1997) to filter out the contribution of standard factors in computing the autocorrelation and calculate the autocorrelation of daily adjusted returns within a quarter.

In Table 8, Panel A, we report estimates from the regression of stock-return autocorrelation on *Top institutional ownership* and controls, including stock and quarter fixed effects. Standard errors are clustered at the stock and quarter level. The results suggest a significantly negative relation between return autocorrelation and ownership by large firms. Interpreting what these coefficients imply about price efficiency is ambiguous. If the autocorrelation of returns is overall negative, the negative estimates imply that the returns of stocks owned by top institutions are even more negatively autocorrelated and, therefore, more noisy. On the other hand, if the autocorrelation of returns is on average positive, the negative sign of the coefficients implies that the prices of stocks owned by large firms are closer to a random walk (zero autocorrelation of returns) and, therefore, more efficient.

We dispel this ambiguity in Panel B of Table 8, using the absolute value of the autocorrelation as the dependent variable. The estimates suggest a significantly positive relation between the absolute value return autocorrelation and large firm ownership (up to the top 20th institution). In combination with Panel A, this finding allows us to conclude that the returns of stocks with more top institutions in their client base are more negatively autocorrelated than the returns of other stocks. In other words, the prices of stocks with higher ownership by larger firms are less efficient, on average. The economic magnitude seems non-negligible. From Column (4) of Panel A, we infer that a one standard deviation increase in the ownership by the top ten institutions is associated with a decrease of 0.5% in the return autocorrelation coefficient.[21]

Overall, these results suggest that stocks with higher ownership by top institutions exhibit less efficient prices than other stocks, even after controlling for ownership by all institutions. This evidence strengthens the case for interpreting the positive impact of large institutions' ownership on volatility as the result of noise.

5.2 Co-movement with Large Institutions' Portfolios

Another way to detect noise in prices induced by large institutions is to look at the co-movement of individual stocks with the other stocks in the portfolios of the top institutions. If large institutions impound common shocks into the prices of the securities that they own, stocks in the same institutional portfolio should co-move beyond the correlation arising from standard factors. The literature has shown convincingly that common institutional ownership modifies the

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[21] Using the statistics from Table 1, Panel B: -0.061 * 0.076 = -0.005. From Table 1, Panel A, the mean autocorrelation in the sample is -8.7%, while the standard deviation is 18.8%. The effect is, therefore, economically large.

correlation structure of returns (Greenwood and Thesmar 2011, Anton and Polk 2014). Here, we ask whether this effect is even stronger for ownership by large institutions.

For each stock-quarter, we compute the beta from the rolling regression of the daily excess return of the stock with respect to the excess return of the top institution's portfolio (excluding the stock itself) within the quarter. Then, we regress this beta on ownership by the large institution while controlling for the factor loadings on the Fama and French (1993) factors and the Carhart (1997) momentum factor, which are also estimated within the quarter from daily returns. In addition to time effects, we include stock fixed effects in the regression as well as various stock characteristics such as the logarithm of size, liquidity, book-to-market, and momentum. Doing so allows us to control for the possibility that institutions prefer stocks with similar characteristics that load on the same set of factors.

In Table 9, the results show unambiguously that the co-movement of stocks with the institutional portfolio increases with the institution's ownership in the stock. A 1% increase in ownership by a large institution contributes 0.01 to 0.02 to the beta of the stock with that institution's portfolio. This finding is consistent with prior evidence in the literature (Greenwood and Thesmar 2011, Anton and Polk 2014). However, we further note that the effect is more sizeable for larger institutions (compare Top 1–Top 5 with Top 6–Top 10). This fact suggests that large institutions impound noise into prices at a greater rate than other institutions, consistent with the hypothesis that the shocks originating from large investors are less diversifiable than other idiosyncratic shocks. In this sense, our findings extend the prior literature. For the purposes of the main question in the paper, the evidence corroborates the view that idiosyncratic shocks spill over from large institutions to asset prices.

6 Conclusion

In this study, we provide novel evidence that large asset managers have a positive causal impact on the volatility of the securities in which they invest. The result is economically significant: a 1% increase in stock ownership leads to an increase in stock volatility of about 12 to 18 basis points, relative to a daily average of 3.5%. This finding does not seem to only be the result of greater information production or faster price discovery. In fact, the presence of large institutions correlates with lower price efficiency, as the stocks in which they trade have higher absolute autocorrelations of returns. In addition, the stocks in the portfolios of large institutions display abnormal return co-movement.

In studying the origins of this effect, we provide evidence suggesting that the trading volume of large institutions generates a large price impact. Moreover, we find that large institutions' trades are, on average, less diversified than the trades of a control group of smaller institutions with the same combined assets, which can explain their greater price pressure. Although large firms' trades become less concentrated over time, the effect of interest remains significant even in the latest years of the sample. Finally, we show that the flows to the funds under the same institutional umbrella are more correlated than the flows to funds belonging to different families. This result provides one potential explanation for why the different units within an institution trade in a less diversified way than a set of independent institutions.

We believe that these results are informative for regulators. The evidence suggests that large institutional investors are more likely to destabilize financial markets than a set of small institutions that trade in a less correlated way. The effect that we find is likely to be exacerbated during times of financial crisis when large trades are executed in an illiquid market. Any policy prescription cannot, however, overlook the beneficial role played by large institutions in terms of economies of scale, information production, corporate governance, and liquidity provision. These other dimensions deserve further investigation to assess the overall impact of large financial institutions on financial markets. Hence, we see the main contribution of our empirical work as drawing attention to the special role played by large institutional investors in today's economy.

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Appendix A. Variable Definitions

Variable	Description	Source
Daily volatility	Standard deviation of the daily log of stock returns within the quarter.	CRSP
log(market cap)	The logged market capitalization of the stock (in $ millions) at the end of the month.	CRSP
1/Price	The inverse of the stock price at the end of the quarter.	CRSP
Amihud ratio	Absolute return scaled by daily dollar volume in $ million, averaged within the quarter. Based on Amihud (2002).	CRSP
Top inst ownership	The % ownership of the large institution, computed as the number of shares owned at the end of the quarter divided by the number of share outstanding for that company.	13F, CRSP
Ownership by all institutions	The % ownership by all institutions, computed as the total number of shares owned by all 13F institutional managers at the end of the quarter, divided by the number of share outstanding.	13F, CRSP
Past 6-month return (q-3 to q-1)	The stock's six-month momentum return over the two quarters prior to analysis.	CRSP
Book-to-market (q-1)	The stock's book value of equity relative to its market value of equity.	CRSP, Compustat
Ownership by bottom institutions	Institutional ownership of the set of the smallest institutions that in aggregate have equity holdings equal to the top 10 institutions.	13F
Same state score	The sum of the indicators of whether the headquarters of the firm and the headquarters of the top institutional investors included in the regression are in the same state.	Compustat, 13F
Greenwood and Thesmar (2011) Fragility	The effective concentration of ownership of a financial asset, weighted by the volatility and correlation of the trading needs of its investors (Greenwood and Thesmar, 2011).	13F, CRSP
Piotroski F-score	A score to determine a firm's financial strength using Piotroski's (2000) F-score methodology.	Compustat
Ohlson O-score	A score to predict financial distress following Ohlson (1980).	Compustat
Altman's Z	Z-score following the formula by Altman (1968) to predict bankruptcy.	Compustat
CHS distress risk	A score developed by Campbell, Hilscher, and Szilagyi (2008) to measure distress risk.	Compustat, CRSP
Fraction of qtrs. with negative income	The fraction of quarters in the last two years in which the firm posted negative earnings.	Compustat
State-level dGDP	The annual growth rate in the state-level gross domestic product (GDP) for the state in which the company resides.	Bureau of Economic Analysis
Combined ownership	Ownership of the large institution that resulted from the 2009 Blackrock-BGI merger.	13F
Post-merger dummy	An indicator for whether the quarter in consideration is in 2010/Q1 or later.	-
ρ(DGTW-adjusted returns(t, t-1))	The daily autocorrelation in stock benchmark-adjusted returns (using Daniel, Grinblatt, Titman, and Wermers, 1997, DGTW, portfolios for the adjustment).	CRSP

Appendix A. Variable Definitions (Cont.)

Variable	Description	Source
Beta of daily returns with those of Top inst. portfolio	Sensitivity of the stock's daily returns to the portfolio of the largest institutional investors, excluding the holdings of the stock.	CRSP, 13F
$Beta_{MKT}$	Sensitivity of the stock's daily returns to the Fama-French (1993) market factor.	CRSP, French's website
$Beta_{SMB}$	Sensitivity of the stock's daily returns to the Fama-French (1993) SMB factor.	CRSP, French's website
$Beta_{HML}$	Sensitivity of the stock's daily returns to the Fama-French (1993) HML factor.	CRSP, French's website
$Beta_{UMD}$	Sensitivity of the stock's daily returns to the Carhart (1997) momentum factor.	CRSP, French's website
Trade by Top institution (0/1)	An indicator variable for whether the trade is carried out by an institution among the top X, where X is specified in the table heading	ANcerno, 13F
Price impact (%)	For a buy trade, the price impact is the difference between the maximum execution price within an order and the open price, divided by the open price. For a sell trade, we change the sign and use the minimum execution price within an order. Orders result from the aggregation of all trades by a given manager on the same day, side (buy or sell), and stock.	ANcerno
Trade size	The number of shares traded by a manager on a given side (buy or sell), stock, day, divided by the total daily trading volume in a stock	ANcerno
Mutual fund flow correlation (i, j)	The correlation between the flows (scaled by total net assets) of two funds over a calendar year.	CRSP Mutual Fund Database
Same management company (i, j)	An indicator as to whether the two funds share the same parent management company.	CRSP Mutual Fund Database

Appendix B. Top Institutional Investors

This table lists all of 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. *Average Long Equity Assets* is the average assets managed by the institution over the time that the institution is in our sample, defined in 2015 dollars. *Average 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
Blackrock Inc	9385	94105	CA	17	2010 Q3	2015 Q3	$1,040,866.94	3.55%	1.1
Bzw Barclays Glbl Invts	92040	94105	CA	24	1990 Q2	1996 Q1	$78,571.35	2.94%	1.3
Barclays Bank Plc	7900	94104	CA	51	1997 Q1	2009 Q3	$480,174.61	5.26%	1.6
Fidelity Mgmt & Research Co	27800	02109	MA	96	1991 Q4	2015 Q3	$427,760.42	13.08%	2.1
Fmr Corp	26590	02109	MA	20	1986 Q1	1990 Q4	$27,215.97	21.02%	3.7
Bankers Tr N Y Corp (Deutsche Bk)	7800	10017	NY	95	1980 Q1	2005 Q2	$75,098.19	5.91%	3.8
State Str Corporation	81540	02111	MA	106	1988 Q2	2015 Q3	$339,939.29	4.32%	4.1
Vanguard Group, Inc.	90457	19482	PA	67	1999 Q1	2015 Q3	$501,869.94	2.57%	4.4
Prudential Ins Co/Amer	72280	07102	NJ	15	1980 Q1	1983 Q3	$6,962.83	11.12%	4.7
College Retire Equities	18265	10017	NY	74	1980 Q1	1998 Q2	$32,609.23	4.77%	4.7
Wells Fargo Bank N.A.	92035	94104	CA	37	1980 Q2	1990 Q1	$22,942.46	4.19%	4.5
Capital Research & Mgmt Co	12740	90071	CA	72	1990 Q3	2008 Q2	$214,521.95	8.81%	4.9
Manufacturers Natl	53690	48226	MI	1	1980 Q1	1980 Q1	$4,623.67	.	5.0
Batterymarch Finl Mgmt	8190	02116	MA	18	1981 Q4	1986 Q1	$9,479.47	11.32%	5.7
Capital World Investors	11836	90071	CA	32	2007 Q4	2015 Q3	$289,717.40	8.16%	5.7
Equitable Companies Inc (Axa)	25610	10014	NY	64	1994 Q2	2010 Q1	$199,050.91	13.03%	6.1
Citicorp	16260	10022	NY	28	1980 Q1	1988 Q1	$8,883.59	13.44%	6.3
Jpmorgan Chase & Company	58835	10017	NY	80	1980 Q1	2015 Q3	$72,844.43	11.58%	6.5
Donaldson Lufkin & Jen	23375	10172	NY	13	1982 Q4	1985 Q4	$10,347.28	21.25%	6.2
Alliance Capital Mgmt	1250	10105	NY	27	1986 Q4	1993 Q2	$23,161.08	14.39%	6.4
T. Rowe Price Associates, Inc.	71110	21202	MD	43	1980 Q1	2015 Q3	$233,657.76	8.98%	6.2
Mellon National Corp (Mellon Bank)	55390	15219	PA	126	1980 Q1	2015 Q3	$131,342.57	7.71%	6.7
Putnam Investment Mgmt, L.L.C.	72400	02266	MA	42	1980 Q3	2003 Q3	$122,707.37	16.42%	7.4
First Interstate Bancorp	29800	90017	CA	19	1981 Q2	1987 Q1	$10,720.55	8.54%	7.5
Sarofim Fayez	76045	77010	TX	10	1980 Q4	1983 Q1	$6,013.41	5.53%	7.7
State Street Resr & Mgmt	81575	02111	MA	12	1982 Q2	1985 Q1	$7,741.61	9.03%	7.8
New York St Common Ret.	63850	10038	NY	30	1986 Q4	1994 Q1	$21,270.73	3.88%	8.2
Capital Research Gbl Investors	11835	90071	CA	25	2007 Q4	2015 Q1	$232,949.11	8.78%	8.3
Calif Public Emp. Ret.	12000	95811	CA	4	1988 Q4	1989 Q3	$16,805.40	8.46%	8.3
Wellington Management Co, Llp	91910	02210	MA	97	1985 Q2	2015 Q3	$159,759.87	11.60%	8.1
Harris Trust & Sav Bank	43680	60640	IL	3	1980 Q1	1980 Q3	$4,557.99	9.33%	8.7
Janus Capital Corporation	48170	80206	CO	5	2000 Q1	2001 Q1	$189,638.67	16.68%	8.8
Morgan Stanley D Witter	58950	10036	NY	23	1997 Q4	2015 Q1	$174,003.77	10.68%	9.3
Travelers (Citigroup Inc)	84900	55102 (10022)	MN (NY)	17	1996 Q2	2005 Q3	$144,162.92	10.61%	9.4
Legg Mason Inc	50160	21202	MD	4	2006 Q3	2007 Q2	$211,065.84	7.96%	9.5
Northern Trust Corp	65260	60603	IL	23	2003 Q4	2015 Q3	$231,661.75	3.14%	9.5
Calif Public Empl Retirm	12090	95811	CA	5	1986 Q2	1987 Q4	$15,388.04	5.05%	9.4
Invesco Ltd	10586	30309	GA	1	2014 Q4	2014 Q4	$292,241.76	8.21%	10.0
Chase Manhattan Corp	15230	10017	NY	2	1980 Q1	1980 Q2	$4,221.70	5.81%	10.0
Goldman Sachs & Company	41260	10282	NY	1	2007 Q3	2007 Q3	$236,162.71	18.61%	10.0

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. The top and second panels within Panel A report stock-quarter level variables. The third panel of Panel A reports mutual fund-year-level variables. The bottom panel in Panel A reports manager-day-stock-level variables and the sample ranges between 1999 and 2010. Panel B presents the mean and standard deviations of stock-level ownership by the top one through top ten largest institutions in each quarter as well as for various groups of large institutions collectively. It also reports statistics on other stock-level variables that are used in the analysis. Panel C presents, by index, the proportion of stocks held by large institutions for the top one through top ten institutions individually as well as for various groups of large institutions collectively. Finally, Panel D presents correlations of key variables used in the analysis. Unless otherwise specified, the sample period is 1980/Q1–2015/Q3. The frequency is quarterly, except for the mutual fund flow panel, which is annually.

Panel A: Summary Statistics of Regression Variables

	N	Mean	Std Dev	Min	p25	Median	p75	Max
Stock-quarter-level sample								
Daily volatility (%) (q)	646,781	3.520	2.540	0.208	1.840	2.800	4.360	24.500
ρ(DGTW-adj ret(t, t-1))	571,734	-0.087	0.188	-0.623	-0.212	-0.076	0.045	0.458
Ownership by all institutions (q-1)	646,781	0.371	0.295	0.000	0.106	0.311	0.600	1.280
1 / price (q-1)	646,781	0.246	0.606	0.005	0.039	0.076	0.197	10.400
Amihud illiquidity (q-1)	646,781	0.366	0.589	0.000	0.006	0.079	0.486	4.330
log(market cap) (q-1)	646,781	5.180	2.070	0.424	3.630	5.020	6.590	11.400
Past 6-month return (q-3 to q-1)	646,781	0.066	0.421	-0.939	-0.161	0.028	0.222	8.140
Book-to-market (q-1)	646,781	0.751	0.658	-0.029	0.335	0.596	0.963	10.300
Ownership by bottom institutions	646,781	0.017	0.032	0.000	0.000	0.005	0.017	0.284
Greenwood and Thesmar Fragility	499,066	0.118	0.195	0.000	0.0139	0.0468	0.122	1.54
Piotroski Financial Statement Score	450,830	4.100	1.710	0.000	3.000	4.000	5.000	9.000
Ohlson O-Score	450,830	-0.030	2.440	-394.000	-1.030	0.177	1.230	111.000
Altman Z-Score	450,830	6.220	34.500	-299.000	2.190	3.660	5.880	8882.000
CHS (Campbell, et al., 2011)	450,830	7.610	5.230	-1469.000	7.200	8.100	8.610	185.000
Fraction of qtrs with negative income	450,830	0.308	0.354	0.000	0.000	0.125	0.571	1.000
2009 Blackrock-BGI Merger: stock-quarter-level								
Daily volatility (%) (q)	31,331	3.004	1.546	0.205	1.940	2.695	3.693	11.131
Combined ownership (q-1)	31,331	0.046	0.030	0.000	0.020	0.049	0.066	0.365
Absolute combined trades (q)	31,331	0.004	0.008	0.000	0.000	0.001	0.004	0.142
Mutual Fund Flows: fund-year-level								
Mutual funds (i, j) correlation	249,665,892	0.030	0.332	-1.000	-0.192	0.028	0.253	1.000
Same management company indicator	249,665,892	0.008	0.088	0.000	0.000	0.000	0.000	1.000
Trade data: day-manager-stock-level								
Price impact (%)	3,017,198	0.212	1.570	-5.820	-0.536	0.117	0.939	6.770
Trade size	3,017,198	0.013	0.037	0.000	0.000	0.001	0.007	0.391
Trade by Top 10	3,017,198	0.111	0.314	0.000	0.000	0.000	0.000	1.000
Trade by Top 20	3,017,198	0.113	0.316	0.000	0.000	0.000	0.000	1.000
Trade by Top 21-30	3,017,198	0.004	0.063	0.000	0.000	0.000	0.000	1.000
Trade by Top 31-50	3,017,198	0.010	0.098	0.000	0.000	0.000	0.000	1.000

Table 1. Summary Statistics (Cont.)

Panel B: Stock Ownership and Stock Characteristics, by Large Institutions

	Top inst ownership		Same state		Beta		Total abs trades	
	N = 646,781		N = 450,830		N = 632,320		N = 435,000	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Top 1	0.018	0.026			0.651	0.713		
Top 2	0.014	0.022			0.638	0.720		
Top 3	0.007	0.015			0.635	0.728		
Top 4	0.007	0.018			0.612	0.722		
Top 5	0.006	0.014			0.602	0.714		
Top 6	0.005	0.013			0.591	0.715		
Top 7	0.005	0.014			0.583	0.718		
Top 8	0.004	0.011			0.581	0.722		
Top 9	0.005	0.012			0.580	0.728		
Top 10	0.005	0.012			0.575	0.729		
Top 3 insts	0.039	0.048	0.294	0.587			0.008	0.011
Top 5 insts	0.052	0.063	0.458	0.807			0.011	0.013
Top 7 insts	0.062	0.073	0.624	1.03			0.013	0.015
Top 10 insts	0.076	0.085	0.854	1.33			0.017	0.019
Top 11-Top 20	0.033	0.045						
Top 21-Top 30	0.020	0.032						
Top 30-Top 50	0.027	0.039						
> Top 10							0.030	0.044

Panel C: Stock Ownership by Large Institutions, by Index

	All stocks		S&P 500		Russell 1000		Russell 2000		Russell 3000	
	Top inst own'p (%)	Top inst (0/1)	Top inst own'p (%)	Top inst (0/1)	Top inst own'p (%)	Top inst (0/1)	Top inst own'p (%)	Top inst (0/1)	Top inst own'p (%)	Top inst (0/1)
Top 1	0.017	0.615	0.029	0.969	0.027	0.935	0.022	0.736	0.024	0.805
Top 2	0.013	0.649	0.025	0.971	0.022	0.941	0.018	0.757	0.019	0.821
Top 3	0.007	0.479	0.021	0.908	0.016	0.854	0.009	0.668	0.011	0.733
Top 4	0.007	0.474	0.017	0.883	0.015	0.814	0.009	0.590	0.011	0.669
Top 5	0.006	0.388	0.015	0.847	0.013	0.769	0.007	0.457	0.009	0.567
Top 6	0.005	0.390	0.012	0.845	0.010	0.766	0.005	0.448	0.007	0.560
Top 7	0.005	0.347	0.011	0.838	0.010	0.741	0.006	0.377	0.007	0.505
Top 8	0.004	0.402	0.010	0.855	0.009	0.770	0.005	0.464	0.006	0.572
Top 9	0.005	0.416	0.010	0.830	0.008	0.760	0.006	0.500	0.007	0.591
Top 10	0.005	0.414	0.009	0.836	0.008	0.764	0.006	0.497	0.006	0.590
Top 3 insts	0.037	0.803	0.075	0.991	0.065	0.985	0.049	0.904	0.055	0.932
Top 5 insts	0.050	0.835	0.107	0.995	0.092	0.991	0.065	0.927	0.074	0.949
Top 7 insts	0.060	0.858	0.130	0.996	0.112	0.994	0.076	0.938	0.089	0.958
Top 10 insts	0.073	0.883	0.159	0.998	0.137	0.996	0.093	0.951	0.108	0.967

Table 1. Summary Statistics (Cont.)

Panel D: Correlation of Key Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	1.00										
(2)	-0.22	1.00									
(3)	-0.22	0.17	1.00								
(4)	-0.27	0.22	0.78	1.00							
(5)	0.42	-0.07	-0.22	-0.28	1.00						
(6)	0.51	-0.39	-0.39	-0.48	0.37	1.00					
(7)	-0.46	0.28	0.60	0.68	-0.44	-0.70	1.00				
(8)	-0.17	0.09	0.03	0.04	-0.15	-0.17	0.16	1.00			
(9)	0.11	-0.10	-0.11	-0.12	0.19	0.32	-0.28	-0.13	1.00		
(10)	-0.01	0.02	0.09	0.26	-0.04	-0.09	0.05	0.00	0.01	1.00	
(11)	-0.15	0.13	0.53	0.56	-0.14	-0.28	0.40	0.02	-0.07	0.14	1.00

(1) Daily volatility (%)
(2) ρ(DGTW-adj ret(t, t-1))
(3) Ownership by Top Ten Insts
(4) Ownership by all institutions (q-1)
(5) 1 / price (q-1)
(6) Amihud illiquidity (q-1)
(7) log(market cap) (q-1)
(8) Past 6-month return (q-3 to q-1)
(9) Book-to-market (q-1)
(10) Ownership by bottom institutions
(11) Greenwood and Thesmar concentration

Table 2. Ownership of Large Asset Managers and Stock Volatility

This table presents ordinary least squares regression results. In Panels A–D, the dependent variable is the stock's *Daily volatility*. *Daily volatility* is computed from daily returns during quarter q. All independent variables are measured during quarter q-1. Panel A uses the *Top inst. ownership* of the largest institutional investors in a given stock as the key independent variable. Panel B replicates the analysis and adds stock fixed effects. Panel C restricts the sample to only S&P 500 stocks. Panel D focuses on financial crises. Crisis periods are the stock market crash in the fourth quarter of 1987; the credit crunch from the first quarter of 1990 until the fourth quarter of 1992; the Russian debt and long-term capital management (LTCM) crisis in the third and fourth quarters of 1998; the dot-com bubble and the September 11 crisis, from the second quarter of 2000 until the third quarter of 2002; and the subprime lending crisis from the third quarter of 2007 until the fourth quarter of 2009. Panel E, focuses on non-crisis quarters. Lastly, Panel F includes the fragility measure (G) of Greenwood and Thesmar (2011) among the controls. The sample period is 1980/Q1–2015/Q3. 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 Asset Managers 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)	0.432***	0.563***	0.573***	0.520***	0.512***	0.226**	0.169
	(3.18)	(5.45)	(6.11)	(6.23)	(4.94)	(1.98)	(1.52)
Daily volatility (q-1)	0.688***	0.688***	0.688***	0.688***	0.688***	0.688***	0.688***
	(53.19)	(53.19)	(53.20)	(53.23)	(53.30)	(53.29)	(53.29)
Ownership by all institutions (q-1)	0.145***	0.115***	0.099***	0.089**	0.137***	0.172***	0.174***
	(4.65)	(3.42)	(3.00)	(2.57)	(4.32)	(5.39)	(5.18)
1 / price (q-1)	0.300***	0.300***	0.299***	0.300***	0.300***	0.300***	0.300***
	(7.13)	(7.12)	(7.11)	(7.11)	(7.13)	(7.14)	(7.13)
Amihud illiquidity (q-1)	0.362***	0.360***	0.359***	0.358***	0.360***	0.362***	0.362***
	(12.71)	(12.64)	(12.61)	(12.56)	(12.64)	(12.70)	(12.72)
log(market cap) (q-1)	-0.119***	-0.121***	-0.122***	-0.122***	-0.120***	-0.118***	-0.118***
	(-19.70)	(-19.82)	(-19.61)	(-19.71)	(-19.82)	(-19.51)	(-19.47)
Past 6-month return (q-3 to q-1)	-0.256***	-0.256***	-0.255***	-0.255***	-0.255***	-0.256***	-0.256***
	(-3.02)	(-3.02)	(-3.02)	(-3.01)	(-3.01)	(-3.03)	(-3.02)
Book-to-market (q-1)	-0.172***	-0.171***	-0.171***	-0.171***	-0.172***	-0.172***	-0.172***
	(-10.50)	(-10.47)	(-10.47)	(-10.45)	(-10.52)	(-10.51)	(-10.55)
Ownership by bottom institutions (q-1)	-0.526***	-0.460***	-0.437***	-0.423***	-0.531***	-0.587***	-0.588***
	(-4.97)	(-4.58)	(-4.31)	(-4.28)	(-5.11)	(-5.53)	(-5.64)
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	646,780	646,780	646,780	646,780	646,780	646,780	646,780
Adj R^2	0.683	0.683	0.683	0.683	0.683	0.683	0.683

Table 2. Ownership of Large Asset Managers and Stock Volatility (Cont.)

Panel B: Ownership by Large Asset Managers and Daily Volatility, with Stock Fixed Effects

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)	0.815***	0.876***	0.922***	0.820***	0.979***	0.478***	-0.039
	(3.53)	(4.48)	(5.73)	(6.02)	(5.41)	(2.98)	(-0.25)
Ownership by all institutions (q-1)	0.151***	0.122**	0.093*	0.080	0.132**	0.196***	0.226***
	(2.69)	(2.09)	(1.69)	(1.41)	(2.10)	(3.23)	(3.53)
1 / price (q-1)	0.603***	0.602***	0.602***	0.602***	0.602***	0.603***	0.603***
	(9.59)	(9.59)	(9.58)	(9.59)	(9.60)	(9.60)	(9.60)
Amihud illiquidity (q-1)	1.484***	1.483***	1.481***	1.481***	1.483***	1.485***	1.485***
	(23.55)	(23.50)	(23.48)	(23.46)	(23.50)	(23.52)	(23.54)
log(market cap) (q-1)	-0.286***	-0.289***	-0.290***	-0.291***	-0.284***	-0.283***	-0.282***
	(-10.57)	(-10.64)	(-10.66)	(-10.84)	(-10.77)	(-10.65)	(-10.65)
Past 6-month return (q-3 to q-1)	-0.111	-0.110	-0.109	-0.108	-0.110	-0.112	-0.112
	(-0.96)	(-0.95)	(-0.94)	(-0.93)	(-0.95)	(-0.96)	(-0.96)
Book-to-market (q-1)	0.005	0.004	0.005	0.005	0.006	0.005	0.006
	(0.18)	(0.16)	(0.17)	(0.18)	(0.23)	(0.19)	(0.21)
Ownership by bottom institutions (q-1)	-1.564***	-1.502***	-1.462***	-1.448***	-1.565***	-1.654***	-1.683***
	(-7.28)	(-7.14)	(-6.88)	(-6.92)	(-7.55)	(-7.73)	(-7.87)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	646,304	646,304	646,304	646,304	646,304	646,304	646,304
Adj R^2	0.670	0.670	0.670	0.670	0.670	0.670	0.670

Table 2. Ownership of Large Asset Managers and Stock Volatility (Cont.)

Panel C: Ownership by Large Asset Managers and Daily Volatility, S&P 500 Stocks

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)	0.868***	0.919***	0.975***	0.777***	0.245	-0.193	-0.702***
	(2.90)	(3.95)	(4.71)	(4.28)	(1.28)	(-0.84)	(-3.82)
Ownership by all institutions (q-1)	-0.065	-0.111	-0.153	-0.151	-0.013	0.032	0.091
	(-0.64)	(-1.04)	(-1.50)	(-1.44)	(-0.12)	(0.30)	(0.86)
1 / price (q-1)	5.489***	5.484***	5.481***	5.494***	5.522***	5.526***	5.520***
	(10.86)	(10.90)	(10.92)	(10.92)	(10.88)	(10.87)	(10.88)
Amihud illiquidity (q-1)	0.253	0.244	0.226	0.219	0.237	0.241	0.243
	(0.72)	(0.69)	(0.64)	(0.62)	(0.68)	(0.68)	(0.69)
log(market cap) (q-1)	-0.077**	-0.080**	-0.082**	-0.082**	-0.077**	-0.076**	-0.076**
	(-2.18)	(-2.26)	(-2.31)	(-2.32)	(-2.19)	(-2.15)	(-2.14)
Past 6-month return (q-3 to q-1)	-0.140	-0.141	-0.140	-0.136	-0.131	-0.133	-0.138
	(-1.45)	(-1.46)	(-1.44)	(-1.42)	(-1.36)	(-1.38)	(-1.43)
Book-to-market (q-1)	0.047	0.047	0.048	0.048	0.047	0.047	0.050
	(1.10)	(1.08)	(1.12)	(1.13)	(1.08)	(1.09)	(1.15)
Ownership by bottom institutions (q-1)	-0.925	-0.749	-0.594	-0.623	-0.979	-1.101	-1.217
	(-0.71)	(-0.58)	(-0.45)	(-0.48)	(-0.76)	(-0.85)	(-0.94)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,113	68,113	68,113	68,113	68,113	68,113	68,113
Adj R^2	0.623	0.623	0.623	0.623	0.623	0.623	0.623

Table 2. Ownership of Large Asset Managers and Stock Volatility (Cont.)

Panel D: Ownership by Large Asset Managers and Daily Volatility during Crises

Dependent variable:	Daily volatility (q) (%)							
Sample:	All Crises				2008-2009			
Institutions:	Top 3	Top 5	Top 7	Top 10	Top 3	Top 5	Top 7	Top 10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top inst ownership (q-1)	0.941*	1.203***	1.363***	1.133***	2.032**	1.798*	1.856**	0.640*
	(1.76)	(2.85)	(3.77)	(4.02)	(2.43)	(2.30)	(3.25)	(1.98)
Ownership by all institutions (q-1)	0.397***	0.341**	0.292**	0.280**	0.730*	0.690	0.629	0.804*
	(3.10)	(2.45)	(2.26)	(2.13)	(1.94)	(1.83)	(1.73)	(2.27)
1 / price (q-1)	0.462***	0.462***	0.462***	0.461***	0.091	0.091	0.091	0.090
	(5.86)	(5.86)	(5.85)	(5.85)	(0.52)	(0.52)	(0.52)	(0.51)
Amihud illiquidity (q-1)	1.400***	1.399***	1.398***	1.397***	0.989***	0.987***	0.988***	0.982***
	(13.73)	(13.74)	(13.73)	(13.71)	(8.77)	(8.83)	(8.82)	(8.70)
log(market cap) (q-1)	-0.391***	-0.394***	-0.397***	-0.397***	-1.042***	-1.040***	-1.043***	-1.041***
	(-5.83)	(-5.91)	(-5.90)	(-5.97)	(-3.79)	(-3.77)	(-3.77)	(-3.77)
Past 6-month return (q-3 to q-1)	-0.486***	-0.485***	-0.483***	-0.482***	-0.177	-0.176	-0.176	-0.175
	(-4.14)	(-4.14)	(-4.12)	(-4.12)	(-1.19)	(-1.18)	(-1.18)	(-1.18)
Book-to-market (q-1)	-0.011	-0.011	-0.011	-0.010	-0.145*	-0.145*	-0.144*	-0.144*
	(-0.31)	(-0.32)	(-0.32)	(-0.30)	(-2.02)	(-2.03)	(-2.02)	(-2.01)
Ownership by bottom institutions (q-1)	-1.953***	-1.852***	-1.775***	-1.767***	-1.058	-1.030	-0.956	-1.114
	(-4.39)	(-4.31)	(-4.01)	(-4.03)	(-1.32)	(-1.27)	(-1.19)	(-1.43)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,077	170,077	170,077	170,077	34,853	34,853	34,853	34,853
Adj R^2	0.684	0.684	0.684	0.684	0.789	0.789	0.789	0.789

Table 2. Ownership of Large Asset Managers and Stock Volatility (Cont.)

Panel E: Ownership by Large Asset Managers and Daily Volatility during Non-Crisis Quarters

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)	0.609***	0.631***	0.698***	0.605***	0.634***	0.283*	0.134
	(3.30)	(4.31)	(5.21)	(4.58)	(3.86)	(1.76)	(1.01)
Ownership by all institutions (q-1)	0.097*	0.077	0.052	0.046	0.093	0.134**	0.141***
	(1.96)	(1.55)	(1.06)	(0.91)	(1.65)	(2.58)	(2.63)
1 / price (q-1)	0.640***	0.640***	0.639***	0.639***	0.640***	0.640***	0.640***
	(8.74)	(8.73)	(8.73)	(8.74)	(8.74)	(8.74)	(8.74)
Amihud illiquidity (q-1)	1.427***	1.425***	1.424***	1.424***	1.426***	1.428***	1.428***
	(22.86)	(22.81)	(22.78)	(22.74)	(22.87)	(22.89)	(22.89)
log(market cap) (q-1)	-0.258***	-0.260***	-0.261***	-0.262***	-0.256***	-0.255***	-0.255***
	(-11.47)	(-11.61)	(-11.60)	(-11.72)	(-11.64)	(-11.48)	(-11.49)
Past 6-month return (q-3 to q-1)	0.096	0.097	0.098	0.098	0.096	0.095	0.095
	(0.87)	(0.88)	(0.88)	(0.89)	(0.87)	(0.86)	(0.86)
Book-to-market (q-1)	-0.072**	-0.072**	-0.072**	-0.072**	-0.071**	-0.072**	-0.072**
	(-2.52)	(-2.53)	(-2.53)	(-2.53)	(-2.49)	(-2.53)	(-2.52)
Ownership by bottom institutions (q-1)	-1.526***	-1.483***	-1.446***	-1.442***	-1.545***	-1.602***	-1.605***
	(-7.86)	(-7.70)	(-7.49)	(-7.47)	(-8.21)	(-8.27)	(-8.29)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	474,697	474,697	474,697	474,697	474,697	474,697	474,697
Adj R^2	0.684	0.684	0.684	0.684	0.684	0.684	0.684

Table 2. Ownership of Large Asset Managers and Stock Volatility (Cont.)

Panel F: Ownership by Large Asset Managers and Daily Volatility, 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)	0.934***	0.905***	1.000***	0.906***	0.972***	0.430**	0.173
	(3.43)	(3.74)	(5.22)	(5.56)	(4.49)	(2.10)	(0.97)
Ownership by all institutions (q-1)	0.167**	0.146**	0.112	0.094	0.155**	0.223***	0.232***
	(2.43)	(2.06)	(1.65)	(1.37)	(2.10)	(3.15)	(3.11)
1 / price (q-1)	0.618***	0.618***	0.617***	0.618***	0.617***	0.618***	0.618***
	(9.77)	(9.77)	(9.76)	(9.77)	(9.77)	(9.77)	(9.77)
Amihud illiquidity (q-1)	1.462***	1.461***	1.460***	1.460***	1.459***	1.461***	1.461***
	(22.79)	(22.76)	(22.75)	(22.74)	(22.71)	(22.73)	(22.74)
log(market cap) (q-1)	-0.338***	-0.340***	-0.342***	-0.342***	-0.337***	-0.336***	-0.336***
	(-10.84)	(-10.86)	(-10.90)	(-11.00)	(-10.95)	(-10.88)	(-10.89)
Past 6-month return (q-3 to q-1)	-0.108	-0.108	-0.107	-0.106	-0.108	-0.110	-0.110
	(-0.96)	(-0.95)	(-0.95)	(-0.94)	(-0.96)	(-0.97)	(-0.97)
Book-to-market (q-1)	-0.012	-0.012	-0.012	-0.012	-0.011	-0.011	-0.011
	(-0.45)	(-0.46)	(-0.46)	(-0.45)	(-0.40)	(-0.42)	(-0.41)
Ownership by bottom institutions (q-1)	-1.568***	-1.529***	-1.484***	-1.465***	-1.573***	-1.660***	-1.670***
	(-6.72)	(-6.63)	(-6.45)	(-6.40)	(-6.93)	(-7.04)	(-7.15)
Greenwood and Thesmar Fragility (q-1)	0.170***	0.169***	0.166***	0.168***	0.186***	0.179***	0.184***
	(5.30)	(5.30)	(5.22)	(5.26)	(5.67)	(5.39)	(5.55)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	495,925	495,925	495,925	495,925	495,925	495,925	495,925
Adj R^2	0.667	0.667	0.667	0.667	0.667	0.667	0.667

Table 3. Instrumenting Large Institutional Ownership with Local Bias

This table presents two-stage least square regression results. The dependent variable is stock-level *Daily volatility*. *Daily volatility* is computed from daily returns during quarter q. The explanatory variable of interest is the stock-level ownership by the top 3, 5, 7, and 10 institutions. The instrument is the *Same state score.* This score is the sum of X indicator variables, each of them denoting whether the stock's headquarters are located in the same state as that of one of the top institutions included in the regression. Panel A reports the first stage, and Panel B shows the second stage. At the bottom of the tables, we report the p-value for the Angrist and Pischke (2009) F-test for the null hypothesis of weak instruments. Panel C presents the second set of results from an analysis containing the fragility measure (G) from Greenwood and Thesmar (2011). The sample period is 1980/Q1–2015/Q3. 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: First Stage: Ownership by Large Institutional Investors and Local Bias

Dependent variable:	Top Inst. Ownership (q-1)			
Institution:	Top 3 insts	Top 5 insts	Top 7 insts	Top 10 insts
	(1)	(2)	(3)	(4)
Same state score	0.001***	0.001***	0.001***	0.001***
	(3.57)	(4.04)	(4.67)	(4.81)
Daily volatility (q-1) (%)	0.000***	0.000***	0.001***	0.001***
	(3.17)	(3.36)	(3.40)	(4.35)
Ownership by all institutions (q-1)	0.089***	0.118***	0.143***	0.179***
	(34.43)	(28.92)	(34.14)	(41.56)
1 / price (q-1)	0.001**	0.001***	0.002***	0.002***
	(2.53)	(3.80)	(5.98)	(5.52)
Amihud illiquidity (q-1)	0.002**	0.004***	0.007***	0.009***
	(2.31)	(5.07)	(6.87)	(8.41)
log(market cap) (q-1)	0.004***	0.007***	0.009***	0.010***
	(11.09)	(14.35)	(16.92)	(15.30)
Past 6-month return (q-3 to q-1)	-0.001**	-0.002***	-0.002***	-0.004***
	(-2.27)	(-4.20)	(-5.61)	(-6.39)
Book-to-market (q-1)	0.001**	0.001**	0.000	-0.000
	(2.59)	(2.22)	(0.94)	(-0.77)
Ownership by bottom institutions (q-1)	-0.177***	-0.251***	-0.298***	-0.359***
	(-25.29)	(-23.93)	(-28.31)	(-30.40)
Piotroski F-score	0.000***	0.000***	0.000***	0.000***
	(4.94)	(5.64)	(4.96)	(5.07)
O-score	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.79)	(-4.38)	(-4.33)	(-4.19)
Altman's Z	-0.000	-0.000	-0.000	-0.000*
	(-0.42)	(-1.07)	(-1.43)	(-1.70)
CHS	-0.000	-0.000**	-0.000	-0.000**
	(-1.62)	(-2.07)	(-1.66)	(-2.13)
Fraction of qtrs with negative income	-0.003***	-0.001	-0.000	-0.001
	(-4.32)	(-1.40)	(-0.28)	(-0.83)
State-level dGDP (q)	-0.006	-0.005	-0.003	-0.005
	(-1.07)	(-0.76)	(-0.46)	(-0.60)
State-level dGDP (q-1)	-0.002	-0.004	-0.004	0.000
	(-0.47)	(-0.61)	(-0.56)	(0.01)
State-level dGDP (q-2)	0.008*	0.001	0.001	0.011
	(1.68)	(0.15)	(0.19)	(1.42)
Calendar quarter FE	Yes	Yes	Yes	Yes
Observations	440,773	440,773	440,773	440,773
Adj R^2	0.605	0.668	0.694	0.721
Angrist and Pischke (2009) p-value	0.00	0.00	0.00	0.00

Table 3. Instrumenting Large Institutional Ownership (Cont.)

Panel B: Second Stage: Instrumented Ownership by Large Institutional Investors and Stock Volatility

Dependent variable:	Daily volatility (q) (%)			
Institution:	Top 3 insts	Top 5 insts	Top 7 insts	Top 10 insts
	(1)	(2)	(3)	(4)
Top Inst. Ownership (IV) (q-1)	36.646***	24.865***	17.062***	11.452***
	(2.79)	(3.05)	(3.04)	(2.67)
Daily volatility (q-1) (%)	0.596***	0.597***	0.601***	0.602***
	(45.83)	(47.81)	(49.87)	(50.23)
Ownership by all institutions (q-1)	-3.068***	-2.740***	-2.231***	-1.840**
	(-2.65)	(-2.91)	(-2.85)	(-2.42)
1 / price (q-1)	0.209***	0.202***	0.196***	0.208***
	(4.88)	(4.84)	(4.73)	(5.18)
Amihud illiquidity (q-1)	0.435***	0.379***	0.377***	0.387***
	(10.60)	(7.47)	(7.38)	(7.73)
log(market cap) (q-1)	-0.233***	-0.266***	-0.248***	-0.216***
	(-4.62)	(-4.64)	(-4.84)	(-4.72)
Past 6-month return (q-3 to q-1)	-0.154**	-0.143*	-0.144*	-0.141*
	(-1.98)	(-1.93)	(-1.87)	(-1.89)
Book-to-market (q-1)	-0.215***	-0.211***	-0.197***	-0.186***
	(-9.67)	(-9.46)	(-10.31)	(-10.71)
Ownership by bottom institutions (q-1)	5.477**	5.229***	4.065**	3.104**
	(2.42)	(2.63)	(2.52)	(2.06)
Piotroski F-score	-0.045***	-0.044***	-0.041***	-0.039***
	(-6.64)	(-7.54)	(-8.03)	(-8.71)
O-score	0.004	0.004	0.002	0.000
	(0.98)	(1.14)	(0.66)	(0.15)
Altman's Z	0.000	0.000	0.000	0.000
	(1.00)	(1.25)	(1.23)	(1.23)
CHS	-0.002*	-0.002*	-0.003**	-0.003**
	(-1.70)	(-1.72)	(-2.13)	(-2.15)
Fraction of qtrs with negative income	0.816***	0.746***	0.723***	0.731***
	(12.69)	(15.70)	(16.89)	(17.86)
State-level dGDP (q)	0.983***	0.898***	0.857***	0.837***
	(3.47)	(3.62)	(3.67)	(3.81)
State-level dGDP (q-1)	0.942***	0.973***	0.939***	0.873***
	(3.60)	(3.87)	(3.82)	(3.70)
State-level dGDP (q-2)	0.206	0.489**	0.490**	0.386*
	(0.77)	(2.12)	(2.26)	(1.82)
Calendar quarter FE	Yes	Yes	Yes	Yes
Observations	440,773	440,773	440,773	440,773

Table 3. Instrumenting Large Institutional Ownership (Cont.)

Panel C: Second Stage: Instrumented Ownership by Large Institutional Investors and Stock Volatility and Including Greenwood and Thesmar's (2011) Fragility Measure

Dependent variable:	Daily volatility (q) (%)			
Institution:	Top 3 insts	Top 5 insts	Top 7 insts	Top 10 insts
	(1)	(2)	(3)	(4)
Top Inst. Ownership (IV) (q-1)	55.254**	29.182**	18.628**	13.075**
	(2.07)	(2.53)	(2.53)	(2.13)
Daily volatility (q-1) (%)	0.588***	0.594***	0.597***	0.597***
	(38.94)	(46.60)	(48.81)	(48.67)
Ownership by all institutions (q-1)	-4.286**	-2.962**	-2.277**	-2.029**
	(-2.02)	(-2.46)	(-2.42)	(-2.00)
1 / price (q-1)	0.233***	0.226***	0.217***	0.227***
	(5.40)	(5.58)	(5.46)	(5.79)
Amihud illiquidity (q-1)	0.520***	0.458***	0.445***	0.442***
	(11.48)	(12.03)	(12.10)	(11.90)
log(market cap) (q-1)	-0.243***	-0.244***	-0.220***	-0.194***
	(-3.52)	(-4.28)	(-4.64)	(-4.45)
Past 6-month return (q-3 to q-1)	-0.174**	-0.176**	-0.181**	-0.179**
	(-2.18)	(-2.34)	(-2.39)	(-2.36)
Book-to-market (q-1)	-0.235***	-0.221***	-0.204***	-0.191***
	(-7.55)	(-8.91)	(-10.26)	(-10.81)
Ownership by bottom institutions (q-1)	7.290*	5.105**	3.691**	3.026*
	(1.87)	(2.20)	(2.08)	(1.67)
Piotroski F-score	-0.050***	-0.046***	-0.042***	-0.040***
	(-5.27)	(-7.00)	(-8.01)	(-8.44)
O-score	0.003	0.002	-0.000	-0.002
	(0.63)	(0.52)	(-0.02)	(-0.56)
Altman's Z	0.000	0.000	0.000	0.000
	(0.35)	(0.77)	(0.64)	(0.59)
CHS	-0.002	-0.003*	-0.003**	-0.003**
	(-1.44)	(-1.70)	(-2.04)	(-2.01)
Fraction of qtrs with negative income	0.874***	0.773***	0.750***	0.757***
	(9.23)	(14.50)	(16.14)	(17.00)
State-level dGDP (q)	1.243***	0.983***	0.875***	0.819***
	(2.95)	(3.53)	(3.62)	(3.57)
State-level dGDP (q-1)	0.886***	0.856***	0.807***	0.749***
	(2.87)	(3.18)	(3.25)	(3.11)
State-level dGDP (q-2)	0.238	0.461*	0.491**	0.336
	(0.69)	(1.72)	(2.01)	(1.41)
Greenwood and Thesmar Fragility (q-1)	-0.944*	-0.480*	-0.275	-0.136
	(-1.66)	(-1.82)	(-1.59)	(-0.95)
	1.219***	1.471***	1.632***	1.644***
Calendar quarter FE	(7.42)	(12.75)	(12.28)	(10.82)
Observations	347,409	347,409	347,409	347,409

Table 4. 2009 Blackrock-BGI Merger

This table presents ordinary least squares regression results. The dependent variable is the *Daily volatility* of the stocks held by large institutional investors. *Daily volatility* is computed from daily returns during quarter q. This test uses the exogenous event of the merger between Blackrock and BGI in 2009 to test the relation between volatility and ownership by large institutions. The key independent variables are *Combined ownership* and *Combined ownership dummy*, which represent the combined ownership of the two institutional investors before and after the merger completion, and their respective interactions with the *Post-merger dummy*. The sample in each column includes the pre-completion quarter (2009/Q4) and several quarters after the completion, as specified. 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.

Dependent variable:	Daily volatility (q) (%)							
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)
Post-merger dummy								
× Combined ownership (q-1)	1.989***	2.074***	2.288***	1.664**	1.663***	1.515***	1.615***	1.793***
	(3.28)	(3.58)	(4.56)	(2.54)	(2.98)	(3.01)	(3.39)	(3.79)
× Ownership by all institutions (q-1)	0.045	0.095*	0.202*	0.210***	0.186**	0.179***	0.244***	0.292***
	(0.66)	(1.78)	(1.95)	(2.58)	(2.53)	(2.64)	(2.99)	(3.58)
× 1 / price (q-1)	-0.010	0.081	-0.081	-0.084	-0.044	-0.050	-0.035	-0.021
	(-0.11)	(0.87)	(-0.48)	(-0.61)	(-0.35)	(-0.43)	(-0.33)	(-0.21)
× Amihud illiquidity (q-1)	-0.005	-0.153	-0.159*	-0.125	-0.154*	-0.143*	-0.249**	-0.278***
	(-0.06)	(-1.23)	(-1.71)	(-1.41)	(-1.70)	(-1.67)	(-2.11)	(-2.60)
× log(market cap) (q-1)	0.031***	0.035***	0.018	0.016	0.019*	0.021**	0.017**	0.010
	(3.52)	(4.26)	(1.29)	(1.41)	(1.78)	(2.20)	(1.99)	(1.01)
× Past 6-month return (q-3 to q-1)	-0.278***	-0.100	-0.092	-0.044	0.010	-0.027	-0.122	-0.169
	(-3.23)	(-0.94)	(-0.98)	(-0.38)	(0.10)	(-0.26)	(-0.97)	(-1.33)
× Book-to-market (q-1)	-0.139***	-0.061	-0.044	-0.069	-0.086**	-0.107**	-0.118***	-0.107***
	(-4.71)	(-1.10)	(-1.08)	(-1.50)	(-2.00)	(-2.41)	(-2.78)	(-2.98)
× Ownership by bottom institutions (q-1)	-0.897**	-0.893**	-0.557	-0.857**	-0.745**	-0.729**	-0.875***	-0.907***
	(-2.02)	(-2.31)	(-1.44)	(-2.16)	(-2.17)	(-2.26)	(-2.62)	(-2.89)
Combined ownership (q-1)	1.213	-2.242	1.618	1.564	1.183	0.618	0.797	1.245
	(0.95)	(-1.21)	(1.03)	(1.32)	(1.16)	(0.66)	(0.94)	(1.42)
Ownership by all institutions (q-1)	-0.147	-0.103	-0.224	-0.432**	-0.462***	-0.474***	-0.378***	-0.355***
	(-0.46)	(-0.40)	(-0.97)	(-2.20)	(-3.36)	(-3.78)	(-2.91)	(-3.13)
1 / price (q-1)	0.476	0.220	0.522*	0.554**	0.596**	0.558**	0.481**	0.564***
	(1.57)	(1.09)	(1.67)	(2.02)	(2.49)	(2.53)	(2.51)	(3.18)
Amihud illiquidity (q-1)	0.539***	0.740***	0.668***	0.716***	0.507***	0.519***	0.448***	0.438***
	(2.74)	(5.92)	(5.46)	(5.41)	(2.75)	(3.39)	(3.29)	(3.50)
log(market cap) (q-1)	0.400***	0.000	-0.119	-0.185	-0.180	-0.185	-0.323**	-0.344***
	(2.81)	(0.00)	(-1.05)	(-1.37)	(-1.36)	(-1.55)	(-2.33)	(-3.07)
Past 6-month return (q-3 to q-1)	0.341***	0.352***	0.298***	0.338***	0.374***	0.392***	0.408***	0.397***
	(7.30)	(9.26)	(6.81)	(6.87)	(7.42)	(8.75)	(9.65)	(10.25)
Book-to-market (q-1)	0.166*	0.199**	0.314***	0.335***	0.363***	0.389***	0.357***	0.403***
	(1.69)	(2.35)	(2.67)	(3.89)	(4.95)	(5.55)	(5.24)	(5.70)
Ownership by bottom institutions (q-1)	-0.651	0.446	0.446	0.114	0.089	0.141	-0.237	-0.234
	(-0.70)	(0.59)	(0.84)	(0.27)	(0.24)	(0.38)	(-0.49)	(-0.54)
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,540	9,859	13,115	16,385	19,627	22,861	26,067	29,226
Adj R^2	0.168	0.165	0.129	0.175	0.167	0.172	0.280	0.303

Table 5. Trade-level Evidence on Price Impact

This table reports estimates from regressions in which the dependent variable is the price impact from trading. We construct the variables in the regression at the day-manager-stock-side level (where side is either buy or sell). The explanatory variables include: an indicator for whether the trade is made by the top 10, 20, 21 through 30, or 31 through 50 institutions; the size of the trade; and the squared size of the trade. For a buy trade, the price impact is the difference between the maximum execution price across all trades within an order and the open price, divided by the open price. For a sell trade, we change the sign and use the minimum execution price within an order. Trade size is the number of shares traded by a manager on a given side (buy or sell), stock, and day, divided by the total daily trading volume in a stock. The regressions include interactions of stock and date fixed effects. The stock-day-side-manager sample ranges between January 1999 and December 2010. t-statistics based on standard errors clustered at the stock and date level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	Price Impact					
Institution:	Top 10 Institutions			Top 20 Institutions		
	(1)	(2)	(3)	(4)	(5)	(6)
Trade by Top institution (0/1)	0.062***	0.034***	0.012	0.057***	0.030***	0.008
	(6.83)	(3.81)	(1.30)	(6.41)	(3.42)	(0.94)
Trade size		1.729***	5.051***		1.734***	5.062***
		(25.82)	(29.05)		(25.85)	(29.08)
Trade size^2			-15.061***			-15.092***
			(-25.35)			(-25.38)
Stock × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,017,198	3,017,198	3,017,198	3,017,198	3,017,198	3,017,198
R^2	0.316	0.316	0.317	0.316	0.316	0.317

Dependent variable:	Price Impact					
Institution:	Top 21-30 Institutions			Top 31-50 Institutions		
	(7)	(8)	(9)	(10)	(11)	(12)
Trade by Top institution (0/1)	-0.308***	-0.301***	-0.301***	-0.350***	-0.353***	-0.360***
	(-10.96)	(-10.70)	(-10.69)	(-13.69)	(-13.74)	(-13.93)
Trade size		1.764***	5.083***		1.775***	5.125***
		(26.32)	(29.64)		(26.44)	(29.84)
Trade size^2			-15.166***			-15.305***
			(-25.85)			(-26.04)
Stock × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,017,198	3,017,198	3,017,198	3,017,198	3,017,198	3,017,198
R^2	0.316	0.316	0.317	0.316	0.317	0.317

Table 6. Large Institutional Investors versus Synthetic Institutions

The table presents evidence on the trade size of large institutions in relation to synthetic institutions. Stock-quarter level absolute values of trades of large institutions are compared to the absolute value of net trades of 99 synthetic institutions made up of randomly drawn smaller institutions with equity holdings equal to that of the large investor. The panel shows the 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.

	%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%

Table 7. Correlation of Mutual Fund Flows and Mutual Fund Ownership

The table presents results from ordinary least squares regressions of the correlation of mutual fund flows on an indicator for membership of the funds in the same family. 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. The variable of interest is an indicator as to whether both funds belong to the same management company. Appendix A provides variable descriptions. t-statistics in parentheses are based on standard errors with three-way clustering: year, fund i, and fund j. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample ranges from 1980 to 2015.

Dependent variable:	Correlation between Fund i and Fund j			
	(1)	(2)	(3)	(4)
Same management company (i, j)	0.034***	0.033***	0.033***	0.033***
	(13.91)	(24.71)	(24.89)	(25.57)
Year FE	Yes	No	Yes	No
Fund i, Fund j FE	No	Yes	Yes	No
Year × Fund i FE, Year × Fund j FE	No	No	No	Yes
Observations	249,665,961	249,665,960	249,665,960	249,665,960
R^2	0.002	0.014	0.016	0.089

Table 8. Large Institutional Ownership and Stock Autocorrelation

This table presents ordinary least squares regression results. In Panel A, the dependent variable is the *Autocorrelation* of the DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers 1997) of stocks held by large institutional investors. In Panel B, the dependent variable is the absolute value of the autocorrelation. The key independent variable is the *Ownership* of the top institutions in the previous quarter. The sample period is 1980/Q1–2015/Q3. 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: Return Autocorrelation

Dependent variable:	ρ(DGTW-adjusted returns(t, t-1)) (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)	-0.041**	-0.048***	-0.035***	-0.061***	-0.056***	-0.020	-0.038***
	(-2.40)	(-3.30)	(-2.71)	(-4.80)	(-4.02)	(-1.33)	(-3.17)
Ownership by all institutions (q-1)	0.044***	0.045***	0.045***	0.050***	0.045***	0.041***	0.043***
	(8.72)	(8.92)	(8.75)	(9.44)	(8.73)	(8.37)	(8.41)
1 / price (q-1)	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	(12.79)	(12.81)	(12.83)	(12.83)	(12.84)	(12.81)	(12.82)
Amihud illiquidity (q-1)	-0.096***	-0.096***	-0.096***	-0.096***	-0.096***	-0.096***	-0.097***
	(-31.78)	(-31.72)	(-31.65)	(-31.72)	(-31.70)	(-31.72)	(-31.74)
log(market cap) (q-1)	0.004***	0.004***	0.004***	0.005***	0.004***	0.004***	0.004***
	(3.87)	(3.98)	(3.92)	(4.23)	(3.83)	(3.73)	(3.75)
Past 6-month return (q-3 to q-1)	0.015***	0.015***	0.015***	0.014***	0.015***	0.015***	0.015***
	(6.90)	(6.89)	(6.89)	(6.87)	(6.90)	(6.93)	(6.90)
Book-to-market (q-1)	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.39)	(-0.37)	(-0.39)	(-0.38)	(-0.44)	(-0.40)	(-0.40)
Ownership by bottom institutions (q-1)	-0.014	-0.018	-0.017	-0.026	-0.015	-0.010	-0.011
	(-0.90)	(-1.15)	(-1.06)	(-1.61)	(-0.93)	(-0.59)	(-0.69)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	571,338	571,338	571,338	571,338	571,338	571,338	571,338
Adj R^2	0.315	0.315	0.315	0.315	0.315	0.315	0.315

Table 8. Large Institutional Ownership and Stock Autocorrelation (Cont.)

Panel B: Absolute Value of Return Autocorrelation

Dependent variable:	ABS(ρ(DGTW-adjusted returns(t, t-1))) (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)	0.048***	0.045***	0.037***	0.047***	0.024***	-0.001	0.005
	(4.73)	(5.13)	(4.92)	(6.30)	(3.16)	(-0.14)	(0.75)
Ownership by all institutions (q-1)	-0.018***	-0.019***	-0.019***	-0.022***	-0.016***	-0.014***	-0.015***
	(-6.76)	(-7.12)	(-7.09)	(-7.82)	(-5.95)	(-5.33)	(-5.30)
1 / price (q-1)	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(-9.93)	(-9.94)	(-9.96)	(-9.98)	(-9.94)	(-9.92)	(-9.93)
Amihud illiquidity (q-1)	0.065***	0.065***	0.065***	0.065***	0.065***	0.065***	0.065***
	(31.17)	(31.13)	(31.07)	(31.11)	(31.11)	(31.09)	(31.09)
log(market cap) (q-1)	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-8.27)	(-8.35)	(-8.33)	(-8.61)	(-8.02)	(-7.96)	(-7.96)
Past 6-month return (q-3 to q-1)	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-6.36)	(-6.32)	(-6.34)	(-6.27)	(-6.38)	(-6.42)	(-6.41)
Book-to-market (q-1)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-3.99)	(-4.01)	(-3.98)	(-4.00)	(-3.89)	(-3.92)	(-3.92)
Ownership by bottom institutions (q-1)	0.002	0.004	0.004	0.008	-0.002	-0.005	-0.005
	(0.19)	(0.44)	(0.40)	(0.89)	(-0.23)	(-0.55)	(-0.50)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	571,338	571,338	571,338	571,338	571,338	571,338	571,338
Adj R^2	0.287	0.287	0.287	0.287	0.287	0.287	0.287

Table 9. Large Institutional Ownership and Stock Co-movement with Institutions' Portfolios

This table presents ordinary least squares regression results. The dependent variable is the beta of each stock-quarter with the portfolio (excluding the stock itself) of the large institution. The beta is computed using daily returns in the current quarter. The key independent variable is *Ownership* by the top institutions in the previous quarter. The sample period is 1980/Q1–2015/Q3. 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.

Dependent variable:	Beta of daily returns with those of top institution's portfolio (q)									
Institution:	Top 1	Top 2	Top 3	Top 4	Top 5	Top 6	Top 7	Top 8	Top 9	Top 10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Top inst ownership (q-1)	1.262***	0.766***	1.608***	0.317**	0.882***	0.335**	0.234*	0.420**	0.562***	0.357**
	(7.41)	(4.35)	(5.37)	(2.07)	(5.05)	(2.30)	(1.97)	(2.48)	(3.40)	(2.36)
Beta$_{MKT}$	0.036***	0.035***	0.035***	0.034***	0.034***	0.032***	0.032***	0.033***	0.032***	0.031***
	(10.91)	(10.40)	(10.35)	(9.96)	(9.85)	(9.75)	(9.74)	(9.87)	(9.52)	(9.05)
Beta$_{SMB}$	0.017***	0.017***	0.018***	0.017***	0.017***	0.017***	0.018***	0.018***	0.018***	0.019***
	(7.78)	(7.64)	(8.05)	(7.89)	(8.00)	(8.05)	(8.25)	(8.38)	(8.23)	(8.99)
Beta$_{HML}$	-0.014***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.012***	-0.013***	-0.012***	-0.012***
	(-8.08)	(-7.69)	(-7.80)	(-7.31)	(-7.62)	(-7.40)	(-7.00)	(-7.35)	(-7.29)	(-7.38)
Beta$_{UMD}$	0.002	0.002	0.001	0.000	0.000	0.001	0.001	0.000	-0.000	-0.000
	(0.81)	(0.89)	(0.61)	(0.17)	(0.05)	(0.30)	(0.35)	(0.03)	(-0.15)	(-0.06)
Ownership by all institutions (q-1)	0.233***	0.254***	0.285***	0.294***	0.301***	0.311***	0.315***	0.329***	0.327***	0.333***
	(9.33)	(10.50)	(11.07)	(11.28)	(12.23)	(12.46)	(12.64)	(12.65)	(12.89)	(12.99)
1 / price (q-1)	0.002	0.001	-0.001	-0.011*	-0.006	-0.007	-0.007	-0.012**	-0.015**	-0.016***
	(0.35)	(0.24)	(-0.15)	(-1.79)	(-0.99)	(-1.22)	(-1.28)	(-2.14)	(-2.44)	(-2.64)
Amihud illiquidity (q-1)	-0.064***	-0.072***	-0.076***	-0.082***	-0.078***	-0.090***	-0.084***	-0.094***	-0.100***	-0.100***
	(-5.74)	(-6.37)	(-6.75)	(-7.08)	(-6.94)	(-8.02)	(-7.22)	(-8.12)	(-8.77)	(-8.80)
log(market cap) (q-1)	0.066***	0.058***	0.045***	0.040***	0.037***	0.027***	0.028***	0.020***	0.015*	0.013*
	(8.93)	(7.79)	(6.05)	(5.39)	(4.89)	(3.72)	(3.70)	(2.71)	(1.93)	(1.71)
Past 6-month return (q-3 to q-1)	0.074***	0.069***	0.068***	0.070***	0.070***	0.070***	0.068***	0.069***	0.067***	0.063***
	(3.49)	(3.19)	(3.16)	(3.27)	(3.30)	(3.40)	(3.57)	(3.29)	(3.13)	(3.81)
Book-to-market (q-1)	0.004	0.002	0.001	-0.000	0.001	-0.004	-0.005	-0.003	-0.001	-0.005
	(0.43)	(0.24)	(0.16)	(-0.02)	(0.09)	(-0.45)	(-0.73)	(-0.43)	(-0.06)	(-0.54)
Ownership by bottom institutions (q-1)	-0.628***	-0.662***	-0.731***	-0.756***	-0.743***	-0.739***	-0.754***	-0.793***	-0.809***	-0.797***
	(-9.47)	(-9.87)	(-10.41)	(-11.03)	(-11.04)	(-10.70)	(-11.16)	(-11.30)	(-11.61)	(-11.22)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	633,923	633,765	633,723	633,695	633,642	633,723	633,828	633,710	633,713	633,680
Adj R^2	0.330	0.320	0.324	0.316	0.323	0.322	0.328	0.331	0.326	0.324

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.

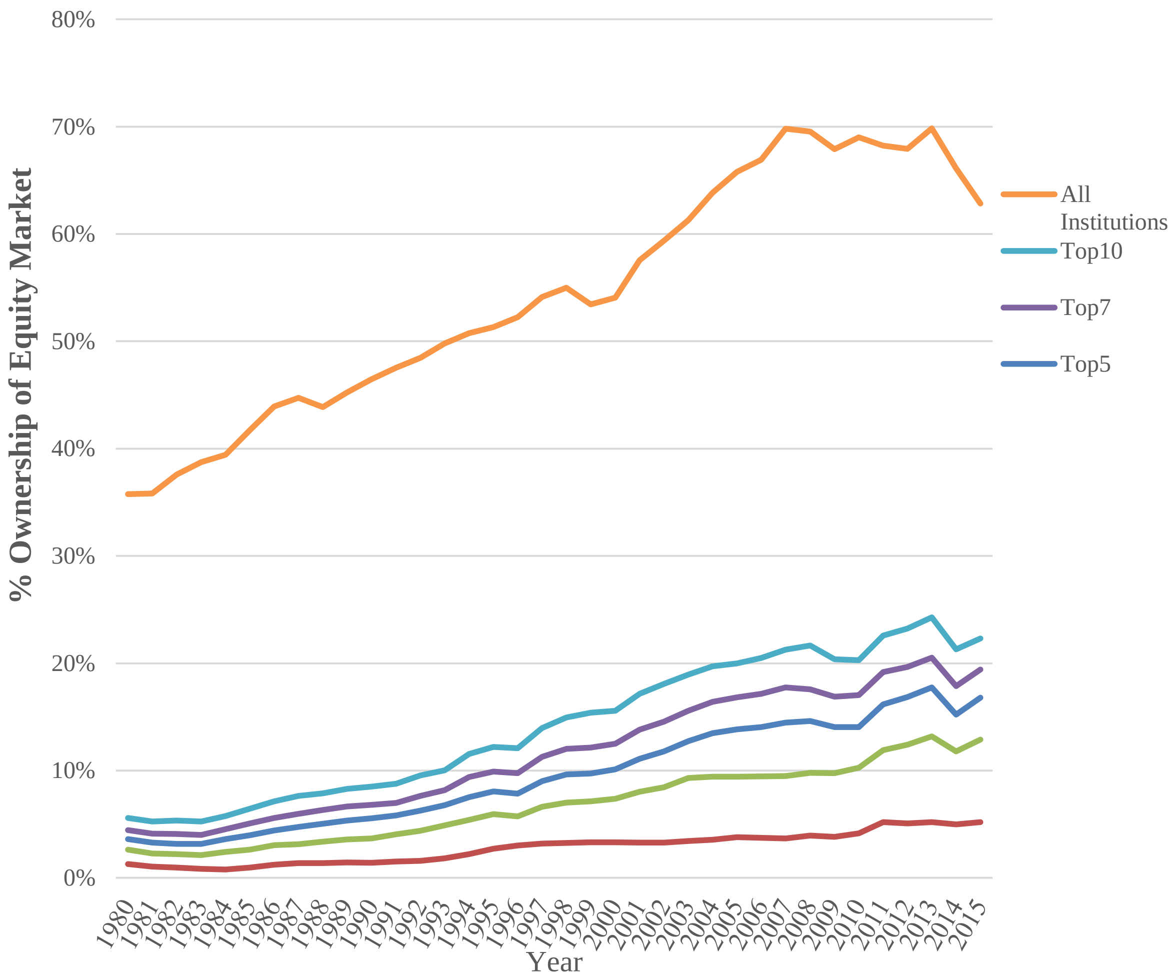

Figure 2. Evolution of Fraction of Stock Traded by the Largest 10 Institutions (Original and Synthetic)

The chart shows the fraction of stocks in CRSP that are traded by large institutions and by synthetic institutions. For each large institutional investor, in each calendar quarter, we create 99 synthetic institutional investors made up of randomly drawn institutions that are not in the top ten. Each of the synthetic institutions has the same equity holdings at the end of the previous quarter as the original institution. Next, we measure the fraction of stocks that are owned by stocks that are traded by the original institutions as well as by the synthetic institutions. Then, we average these fractions across the top original institutions and across the synthetic institutions.

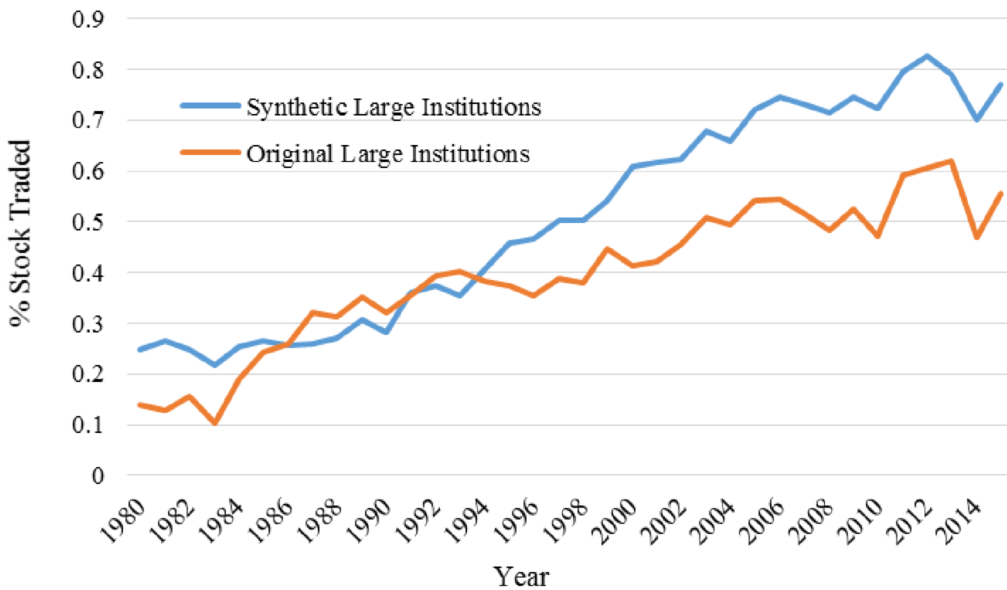

Figure 3. Evolution of Large Institutions' Relative Trade Size

The chart shows the size of trades of large institutions relative to synthetic institutions with the same total equity holdings. For each large institutional investor, in each calendar quarter, we create 99 synthetic institutional investors made up of randomly drawn institutions that are not in the top ten. Each synthetic institution has the same equity holdings at the end of the previous quarter as the original institution. Then, we sort the absolute net trades of the 100 institutions in each stock (99 synthetic institutions and one original institution) and record the percentile in which the original institution is within the group. Stock-quarter-institutions in which there was no trade by the institution are excluded; thus, the analysis is conditioned on the large institution trading in the particular stock-quarter. We perform this exercise for the largest ten institutions for each quarter. The chart reports the average fraction of absolute trades that are larger than the 50^{th}, 90^{th}, 95^{th}, and 99^{th} percentile in each quarter. The dashed lines represent the null hypothesis, that the likelihood of having a trade larger than X^{th} percentile equals (1-X), i.e., generated by a uniform distribution. The y-axis of the plot uses a logarithmic scale.