What Does Stock Ownership Breadth Measure?[*]

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Abstract

Using holdings data on a representative sample of *all* Shanghai Stock Exchange investors, we show that increases in the fraction of market participants who own a stock predict low returns: highest change quintile stocks underperform lowest quintile stocks by 23 percent per year. This is consistent with ownership breadth primarily reflecting popularity among noise traders rather than the amount of negative information excluded from prices by short-sales constraints. But stocks in the top decile of wealth-weighted *institutional* breadth change outperform the bottom decile by 8 percent per year, suggesting that breadth measured among sophisticated institutional investors who cannot short does reflect missing negative information. The profitability of institutional trades against retail investors is almost entirely explained by their correlations with retail and institutional breadth changes.

What should we infer about future returns when we see a large number of investors buying a stock they had previously not owned, or a large number of investors completely liquidating their holdings of a stock? In this paper, we test how changes in ownership breadth—the fraction of market participants with a long position in a given stock—predict the cross-section of stock returns.

Chen, Hong, and Stein (2002) (hereafter CHS) argue that when an investor holds no long position in a stock, he is likely to have negative information about the stock's fundamental value. If the investor cannot sell short, this negative information is only partially incorporated into the stock's price. Thus, when few short-sales-constrained investors are long a stock—that is, when ownership breadth is low among such investors—there is a large amount of negative news missing from the stock's price, and the stock's future returns will be low.[1]

An alternative theory of ownership breadth is that many people owning a stock reflects widespread over-optimism about the stock rather than the absence of hidden negative information. Lewis (1989) writes: "The first thing you learn on the trading floor is that when large numbers of people are after the same commodity, be it a stock, a bond, or a job, the commodity quickly becomes overvalued." According to this view, future returns will be low when ownership breadth in the general investor population is high.

Empirically testing these theories is challenging because comprehensive ownership data are usually not available at high frequency. Even when ownership data are available, it is often unclear which investors are unable to short, and thus impossible to measure ownership breadth among the population relevant to the CHS theory: all short-sales-constrained investors and no unconstrained investors. Previous empirical tests of ownership breadth have measured ownership breadth among U.S. mutual funds, which are representative of neither all U.S. investors nor all short-sales-constrained U.S. investors. The mismatch between available data and theory may explain why the evidence on ownership breadth has been mixed to date. Because ownership breadth *level* is close to a permanent characteristic for a stock, CHS argue that focus should be placed on ownership breadth *changes*—essentially controlling for a stock fixed effect. CHS find

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[1] Most theoretical models find that short-sales constraints lead to overvaluation (e.g., Miller (1977), Harrison and Kreps (1978), Allen, Morris, and Postlewaite (1993), Scheinkman and Xiong (2003)), but there are exceptions. For example, Diamond and Verrecchia (1987) argue that short-sales constraints do not bias stock prices on average when investors correctly anticipate that pessimistic investors are sitting on the sidelines. Bai, Chang, and Wang (2006) show that, depending on the relative importance of informed versus uninformed trading motives, short-sales constraints can increase, decrease, or have no impact on stock prices.

that cross-sectionally, stocks that are held by fewer mutual funds this quarter than last quarter subsequently underperform stocks with mutual fund ownership breadth increases from 1979 to 1998. But Nagel (2005) expands the CHS sample by five years and finds that there is no relationship on average between mutual fund ownership breadth changes and future returns over the longer sample.[2]

We use a new holdings dataset from the Shanghai Stock Exchange (SSE) that is uniquely suited to testing the theories on the relationship between ownership breadth and future returns. The investors in the data are a random, survivorship-bias-free sample of *all* investors in the SSE. During our 1996 to 2007 sample period, short sales were strictly prohibited in China, and there was minimal equity derivatives activity.[3] Therefore, we have no difficulty identifying which investors in our sample are short-sales-constrained; all of them are.

We find, in sharp contrast to the CHS prediction, that high breadth change stocks subsequently *underperform* low breadth change stocks when we define ownership breadth as the percent of all market participants who have a long position in a stock, giving equal weight to every investor. The annualized difference in the four-factor alpha between the highest and lowest quintiles of equal-weighted total breadth change (which is not public information, although proxies could conceivably be constructed from publicly observable data or purchased from retail brokerages) in the first month after portfolio formation is –23 percent, with a *t*-statistic of 9.7. Abnormal returns are present on both the long and short sides of the hypothetical zero-investment portfolio and persist for five months after portfolio formation.

However, as we put more weight on sophisticated investors in our breadth measure, the results change. When we redefine breadth change so that investors are weighted by their lagged stock market wealth, de-emphasizing the small retail investors that dominate the equal-weighted total breadth measure, the annualized four-factor alpha difference between the highest and lowest breadth change portfolios attenuates to –5 percent (still statistically significant). Further restricting the wealth-weighted breadth change sample to institutions, we reproduce the original CHS result in a completely new sample: highest-decile wealth-weighted institutional breadth

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[2] Cen, Lu, and Yang (2011) find that mutual fund breadth changes tend to negatively predict returns when the Baker and Wurgler (2006, 2007) sentiment index experiences large absolute movements. Lehavy and Sloan (2008) find that U.S. mutual fund ownership breadth change is positively autocorrelated, and that controlling for future breadth changes, current breadth change negatively predicts future returns.

[3] There were no equity derivatives prior to the end of 2005. From 2005 to 2007, eleven Shanghai Stock Exchange companies (out of over 800 total listed companies) were allowed to issue put warrants. See Xiong and Yu (forthcoming) for more details on these warrants.

change stocks outperform lowest-decile wealth-weighted institutional breadth change stocks. The annualized difference in the four-factor alphas is 8 percent, with a *t*-statistic of 2.6.

These results suggest that when ownership breadth is measured within the population of sophisticated investors that observe unbiased signals of the stock's fundamental value but cannot short, it functions as the CHS theory predicts, primarily reflecting how much negative information is not in the stock price due to short-sales constraints. The CHS model does not have noise traders in it, so it no longer applies once ownership breadth is measured over a population of predominantly unsophisticated retail investors. Among retail investors, breadth behaves more like the theory recounted by Lewis (1989), correlating negatively with future risk-adjusted returns. Retail ownership breadth changes are negatively correlated with a stock's contemporaneous return. Therefore, to the extent that retail investors cause misvaluation (instead of simply signaling misvaluation or the loading on an unidentified risk factor), it seems that they do so by leaning against price movements and delaying full price adjustment to fundamental news.

Studying breadth changes provides insight into the nature of institutions' profits from trading against individuals. On average, institutional trades against retail investors are profitable before transactions costs; if a stock's month-over-month change in the log fraction of shares owned by institutions is one standard deviation higher, its abnormal return in the subsequent month is 3.5 percent higher on an annualized basis. But the significance of institutional ownership percentage changes disappear once we control for equal-weighted retail breadth changes and wealth-weighted institutional breadth changes, while both breadth change measures remain significant return predictors. This result indicates that how many shares in aggregate change hands between institutions and individuals does not matter as much as how many of each investor type start and end with holdings of the stock, thus demonstrating the value of disaggregated investor-level data for forecasting future returns.

Because we only have ownership data from China, we have no direct evidence on the extent to which our results generalize to other countries, just as any empirical study using only U.S. data cannot draw any conclusions about whether its results extend to non-U.S. markets. We believe that even if our results were to apply only to China, they are of general interest given the significance of the Chinese stock market, which had 139 million investment accounts at year-end 2007 (China Securities Regulatory Commission (2009)) and the second-largest market

4

capitalization among all national stock markets at year-end 2010. Although much of our data come from a time when the Chinese stock market was quite young, all of our results hold in the second half of our sample period, suggesting that they continue to apply to China's market today.

Nevertheless, similarities between China and other markets in retail investor behavior and stock return patterns give us some reason to think that ownership breadth operates in the same way outside of China. Chinese retail investors exhibit the disposition effect, excessive trading, home bias, and under-diversification, just as U.S. investors do (Chen et al. (2007), Feng and Seasholes (2008)). Chen et al. (2010) test 18 variables that have been shown to predict cross-sectional stock returns in the U.S. market and find that in the 1995 to 2007 period, all 18 variables' point estimates in univariate Fama-MacBeth (1973) regressions have signs consistent with the U.S. evidence, and five are statistically significant, compared to eight significant coefficients for the U.S. markets during this same period.

In addition to the literature on ownership breadth, our paper is related to research that attempts to empirically detect the price impact of short-sales constraints,[4] research that seeks to identify the impact individual investors have on prices, and research on the portfolio performance of institutional versus individual investors.[5]

The remainder of the paper is organized as follows. Section I describes our data. Section II defines the variables we use in the analysis. Section III presents the main tests of ownership breadth's ability to predict the cross-section of stock returns. Section IV shows how returns, breadth, and institutional ownership behave around the formation date of portfolios sorted on breadth change, which gives us insight into the decisions that result in breadth changes and why breadth changes might affect returns. Section V explores the relationship between breadth changes and changes in institutional ownership. Section VI investigates the extent to which ownership breadth changes predict future returns via a Merton (1987) investor recognition

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[4] These studies have adopted a number of proxies to measure short-sales constraints, such as analyst forecast dispersion (Diether, Malloy, and Scherbina (2002), Yu (2009)), short interest (Asquith, Pathak, and Ritter (2005), Boehme, Danielsen and Sorescu (2006)), the introduction of traded options (Figlewski and Webb (1993), Danielsen and Sorescu (2001), Mayhew and Mihov (2005)), and lending fees (Jones and Lamont (2002), D'Avolio (2002), Reed (2002), Geczy, Musto, and Reed (2002), Mitchell, Pulvino, and Stafford (2002), Ofek and Richardson (2003), Ofek, Richardson, and Whitelaw (2004), Cohen, Diether, and Malloy (2007)).

[5] See, for example, Gruber (1996), Daniel, Grinblatt, Titman, and Wermers (1997), Zheng (1999), Chen, Jegadeesh, and Wermers (2000), Frazzini and Lamont (2008), Kaniel, Saar, and Titman (2008), Barber, Lee, Liu, and Odean (2008), Kelley and Tetlock (2010), and Barber, Odean, and Zhu (forthcoming).

channel, and Section VII discusses the different implications that ownership initiations versus discontinuations have for future returns. Section VIII concludes.

I. Data description

Our ownership breadth data come from the Shanghai Stock Exchange (SSE). At the end of 2007—the last year of our sample period—the 860 stocks traded on the SSE had a total market capitalization of $3.7 trillion, making it the world's sixth-largest stock exchange behind NYSE, Tokyo, Euronext, Nasdaq, and London. China's other stock exchange, the Shenzhen Stock Exchange, had a $785 billion market capitalization at year-end 2007. By year-end 2010, China's stock market had the second-largest market capitalization among all countries of the world, behind only the U.S.

To trade on the SSE, both retail and institutional investors are required to open an account with the Exchange. Each account uniquely and permanently identifies an investor, even if the account later becomes empty. Investors cannot have multiple accounts. The data assembled by the Exchange for this paper consists of the entire history of SSE tradable[6] A-share[7] holdings from January 1996 to May 2007 for a representative random sample of all accounts that existed at the end of May 2007. Since there are far fewer institutional accounts than retail accounts, the Exchange over-sampled institutional investors in order to ensure that a meaningful number of institutional accounts were extracted.[8] The market-wide statistics computed from these account data are reweighted to adjust for the over-sampling of institutional investors. The sample contains both currently active and inactive accounts, so there is no survivorship bias, and in expectation, a constant fraction of the accounts extant at any date are represented. The number of accounts in the sample grows from 36,349 retail accounts and 360 institutional accounts to 384,709 retail accounts and 20,727 institutional accounts from January 1996 to May 2007.

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[6] Non-tradable shares have the same voting and cashflow rights as tradable shares and are typically owned directly by the Chinese government ("state-owned shares") or by government-controlled domestic financial institutions and corporations ("legal person shares"). Beginning in April 2005, non-tradable shares began to be converted to tradable status. Converted tradable shares were subject to a one-year lockup, and investors holding more than a 5 percent stake were subject to selling restrictions for an additional two years. Dropping returns starting in May 2006 (the month after the first formerly non-tradable shares became liquid and thus begin to appear in our holdings data) does not qualitatively affect our breadth portfolio alpha estimates in Table 3, except that in the shorter sample, the long-short wealth-weighted institutional breadth change portfolio's one-factor alpha is significant at the 10 percent level and the four-factor alpha is significant at the 5 percent level.

[7] A shares, which only domestic investors could hold until 2003, dominate the SSE. For example, at year-end 2007, A shares constituted over 99 percent of SSE market capitalization.

[8] Further details of the sampling process can be obtained from the authors.

Holdings data are aggregated at the Exchange into stock-level measures. The aggregation is carried out under arrangements that maintain strict confidentiality requirements to ensure that no individual account data are disclosed.

We obtain stock return, market capitalization, and accounting data from the China Stock Market & Accounting Research Database (CSMAR).

II. Variable definitions

Following CHS, we define the equal-weighted total ownership breadth change of stock i in month t in the following way. We first restrict the sample to investors who have a long position in at least one SSE stock at the end of both $t – 1$ and t. This restriction ensures that the breadth change measure captures only the trading activity of existing market participants, rather than changes in the investor universe due to new market participants entering and institutions dissolving.[9] Equal-weighted total ownership breadth change is the difference between the end of $t – 1$ and the end of t in the fraction of these subsample investors who own stock i. We obtain equal-weighted retail breadth change and equal-weighted institutional breadth change by further restricting the investor subsample to retail investors or institutional investors. Stocks almost never have an empty set of retail owners in our sample, but zero ownership is more frequent within our institutional sample, particularly among small-cap stocks. At each time period, we do not calculate breadth change for stocks that have zero owners in the relevant subsample at either $t – 1$ or t, since the breadth change measure we obtain would be censored.

A stock's equal-weighted total ownership breadth increases when (1) one investor partially liquidates her position in the stock to sell to one or more investors who previously did not own the stock, or (2) one investor completely liquidates her position by selling her shares to two or more investors who previously did not own the stock. Note that market clearing does *not* constrain a stock's equal-weighted total ownership breadth change to be zero.

If equal-weighted breadth change is negatively correlated with future returns because it measures the enthusiasm of dumb money, then de-emphasizing small investors—who are likely

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[9] Portfolio returns are quite similar if we instead require that investors have a long position at either $t – 1$ or t. When we construct wealth-weighted breadth change, described later in this section, using this alternative sample definition, we weight investors that are not in the market at $t – 1$ by their stock market wealth at the end of t.

to be less sophisticated[10]—in the breadth change measure should attenuate this negative relationship. We thus additionally use an alternative measure of ownership breadth not found in CHS that weights investors by the value of their SSE portfolio at the beginning of the month. To calculate wealth-weighted total ownership breadth change at t, we again restrict the sample to investors who have a long position in at least one SSE stock at the end of both $t-1$ and t. Wealth-weighted ownership breadth change is

$$\frac{\displaystyle\sum_{v \in V_{i,t}} W_{v,t} - \sum_{v \in V_{i,t-1}} W_{v,t}}{\displaystyle\sum_{v \in A_t} W_{v,t}} \tag{1}$$

where $W_{v,t}$ is the SSE stock portfolio value of investor v at month t's market open, $V_{i,t}$ is the set of subsample investors who held stock i at the end of month t, and A_t is the entire subsample of investors who owned at least one SSE stock at the end of both $t-1$ and t. Wealth-weighted retail breadth change and wealth-weighted institutional breadth change are defined analogously over their respective investor populations.

Breadth change can be decomposed into the variables IN and OUT. Equal-weighted IN is the percent of subsample investors who had a zero position in stock i at the end of $t-1$ and a positive position at the end of t. Equal-weighted OUT is the percent of subsample investors who moved from a positive position to a zero position in stock i between the ends of $t-1$ and t. By construction, equal-weighted breadth change is equal-weighted IN minus equal-weighted OUT. Wealth-weighted IN and OUT are defined analogously. For example, wealth-weighted IN is the month t opening SSE stock portfolio value of subsample investors who moved from a zero position to a positive position in stock i between $t-1$ and t divided by the month t opening SSE stock portfolio value of all subsample investors.

Our main cross-sectional analysis involves evaluating the return performance of portfolios formed on breadth changes. We estimate four-factor alphas, where the factor portfolio returns capture CAPM beta, size, value, and momentum effects. The market portfolio return is the composite Shanghai and Shenzhen market return, weighted by tradable market capitalization. The riskfree return is the demand deposit rate. We construct size and value factor returns (SMB

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[10] Small investors have fewer resources with which to gather information. Natural selection arguments such as that of Friedman (1953) may also lead to rational individuals becoming over-represented among wealthy investors. However, Yan (2008) shows that the natural selection mechanism does not robustly reduce irrational investors' wealth share.

and HML, respectively) for the Chinese stock market according to the methodology of Fama and French (1993), but using the entire Shanghai/Shenzhen stock universe to calculate percentile breakpoints. We form SMB based on total (i.e., tradable plus non-tradable) market capitalization and HML based on the ratio of book equity to total market capitalization, weighting stocks within component sub-portfolios by their tradable market capitalization.[11] We construct the momentum factor portfolio MOM following the methodology described on Kenneth French's website. We calculate the 50th percentile total market capitalization at month-end $t - 1$ and the 30th and 70th percentile cumulative stock returns over months $t - 12$ to $t - 2$, again using the entire Shanghai/Shenzhen stock universe to calculate percentile breakpoints. The intersections of these breakpoints delineate six tradable-market-capitalization-weighted sub-portfolios for which we compute month t returns. MOM is the equally weighted average of the two recent-winner sub-portfolio returns minus the equally weighted average of the two recent-loser sub-portfolio returns.

We control for other possible predictors of returns using Fama-MacBeth (1973) regressions, where the predictor variables are the stock's breadth change (defined in various ways), log of total market capitalization, book-to-market ratio (the value at year-end $\tau - 1$ is used as the predictor from July of year τ through June of year $\tau + 1$), return during the last year excluding the prior month, return during the prior month, sum of monthly turnover during the prior quarter, change in the log percent of tradable A shares owned by institutions during the prior month (as measured in our ownership data), Amivest liquidity ratio (described further below) during the prior month, shadow cost of incomplete information, and two dummies for whether the stock's share trading volume during the prior week was in the top tenth or bottom tenth of the ten most recent weeks (Gervais, Kaniel, and Mingelgrin, 2001). We operationalize the Amivest liquidity ratio as the sum of the stock's yuan trading volume over one month divided by the sum of the stock's absolute daily returns over that month. Higher values of the liquidity ratio correspond to lower price impacts of trading, and hence higher liquidity. The shadow cost of incomplete information, λ, captures abnormal returns due to Merton's (1987) "investor recognition hypothesis" that investors neglect to hold stocks they are unaware of, causing the investors who do hold these neglected stocks to sacrifice diversification and hence demand a

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[11] Whenever possible, we use the book equity value that was originally released to investors. If this is unavailable, we use book equity that has been restated to conform to revised Chinese accounting standards.

higher expected return. Investor recognition is closely related to ownership breadth changes and so should be controlled for. We adopt the operationalization of λ used by Bodnaruk and Ostberg (2009):

$$\lambda_{it} = 2.5\sigma_{it}^2 x_{it} \frac{1 - M_{it}}{M_{it}} \tag{2}$$

where 2.5 is an arbitrary constant representing aggregate investor risk aversion, σ_{it}^2 is the variance of the residuals from regressing stock i's excess monthly returns on Chinese market excess returns from month $t - 35$ to month t; x_{it} is stock i's tradable A-share market capitalization as a fraction of total Chinese tradable A-share market capitalization at month-end t; and M_{it} is the number of investors holding stock i at month-end t divided by the total number of investors at month-end t. In calculating M_{it}, we define "total number of investors" as all investors with at least one long SSE position at t (and do not condition on $t - 1$ holdings).

Table 1 shows summary statistics for the variables used in the cross-sectional analysis. Because the number of stocks listed on the SSE expanded rapidly during our sample period, we adopt the following procedure in order to keep later time periods from dominating the summary statistics. We calculate separately for each month the mean and standard deviation of each variable. The table reports the time-series average of these monthly mean and standard deviation series.

The summary statistics for equal-weighted retail breadth change are nearly identical to those for equal-weighted total breadth change, since retail investors vastly outnumber institutions. Because institutions have disproportionately large stock holdings, *wealth*-weighted total breadth changes do not follow wealth-weighted retail breadth changes nearly as closely.

III. Main return prediction tests

A. Forecasting one-month-ahead returns

We test the ability of breadth changes to predict the cross-section of returns by using breadth changes to form portfolios. Following CHS, at the end of each month t, we sort stocks into tradable market capitalization quintiles, and then calculate breakpoints within each size quintile based on breadth change during t. We weight stocks by tradable market capitalization within each size × breadth change sub-portfolio. The volatility of breadth change increases with firm size, which is why CHS and we calculate different breadth change breakpoints for each size

quintile; otherwise, large firms would dominate the extreme quintiles of breadth change. To form the "Quantile n" portfolio, we equally weight across size quintiles the five nth quantile breadth change sub-portfolios, and hold the stocks for one month before re-forming the portfolios at the end of month $t + 1$.

Table 2 shows the breadth change portfolios' raw excess returns and alphas generated by time-series regressions. The left half of Panel A shows that returns decrease monotonically with equal-weighted total breadth change. On a raw-return basis, the lowest quintile outperforms the highest quintile by 204 basis points per month, or 24.5% per year, with a t-statistic of 10.2. The lowest quintile has an annualized Sharpe ratio of 1.11, and a (non-investable) zero-investment portfolio that holds the lowest quintile long and the highest quintile short has a Sharpe ratio of 2.97. In comparison, during this 137-month period, the Sharpe ratio of all Shanghai Stock Exchange A shares weighted by tradable market capitalization was 0.77, and the Sharpe ratio of the U.S. CRSP value-weighted index was 0.49.

The return differential between the lowest and highest breadth change quintiles barely falls to 202 basis points per month (24.2% per year) when we adjust for CAPM beta risk, and to 194 basis points per month (23.3% per year) with a t-statistic of 9.7 when we additionally adjust for size, value, and momentum effects.[12] Abnormal returns come not only from underperformance in the highest total breadth change portfolio (which cannot be shorted), but also from outperformance in the lowest total breadth change portfolio, which has a significant positive four-factor alpha of 112 basis points per month (13.4% per year).

These results are contrary to the CHS model, which predicts that future returns are *increasing* in ownership breadth, since high breadth means fewer investors with bad news are sitting on the sidelines. Instead, the results appear consistent with stocks becoming overvalued when they gain popularity among noise traders and undervalued when they lose popularity among noise traders.[13]

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[12] The average of the long-only test portfolio alphas are not approximately zero mainly because the test portfolios contain only Shanghai Stock Exchange stocks, whereas our factor portfolios contain both Shanghai and Shenzhen Stock Exchange stocks.

[13] Although the model of Bai, Chang, and Wang (2006) has only one risky asset and cannot be used to analyze cross-sectional returns directly, their intuition could potentially lead to the implication that ownership breadth increases should predict lower future returns through a short-sales constraint channel: A breadth increase implies that informed investors' short-sales constraints are less binding, causing the stock price to be more informative, so uninformed investors become more certain about the stock's future payoffs and require lower returns. However, if institutions are the informed investors in the market, then our finding that institutional breadth increases lead to higher future returns is the opposite of what the above story predicts.

The right half of Table 2, Panel A provides evidence supportive of the story that equal-weighted total breadth changes negatively predict returns because they reflect the enthusiasm of noise traders. If wealthy investors are less likely to be noise traders, then weighting breadth changes by investor wealth should decrease the spread between high and low breadth change stocks. Indeed, the raw return difference between the lowest and highest breadth change quintiles falls to 36 basis points per month (4.3% per year) when we use wealth-weighted total breadth changes to form portfolios, although this difference remains significant at the 5% level. Adjusting the difference by the one-factor or four-factor model yields slightly larger and still-significant alphas: 45 basis points and 42 basis points per month (5.4% and 5.0% per year), respectively.

Further evidence in favor of the noise trader story comes from Panels B and C of Table 2, which show returns and alphas of portfolios formed from sorts on retail or institutional breadth changes. In Panel B, paralleling the sorts on total breadth changes, we sort stocks into quintiles based on retail breadth changes. For the portfolios based on institutional breadth changes in Panel C, however, our breadth change breakpoints are the 10th and 90th percentiles instead of the 20th, 40th, 60th, and 80th percentiles. This is because a large number of stocks every month have an equal-weighted institutional breadth change equal to zero.[14]

It seems plausible that institutions are less likely to be noise traders than individuals, which suggests that institutional breadth change should not be a contrarian indicator. We do in fact see in the left half of Panel C that stocks experiencing large equal-weighted institutional breadth increases do not significantly underperform stocks experiencing large equal-weighted institutional breadth decreases. The negative relationship between equal-weighted total breadth changes and future returns in Panel A is entirely driven by retail investors; the returns of portfolios formed on equal-weighted retail breadth changes in the left half of Panel B are very close to those of portfolios formed on equal-weighted total breadth changes. As we previously noted in Section II, equal-weighted total breadth change and equal-weighted retail breadth change are almost identical due to the large number of retail investors.

Moving to wealth-weighted breadth changes among investor subsamples, we find that the increased emphasis on institutions in the wealth-weighted total breadth change measure is not the

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[14] Out of $137 \times 3 \times 5 = 2{,}055$ potential subportfolio-months, there is an empty equal-weighted institutional breadth change subportfolio 11 times and an empty wealth-weighted institutional breadth change subportfolio three times. When a subportfolio is empty, we exclude its return and average over the non-empty subportfolios.

only reason why wealth-weighting attenuates the negative relationship between total breadth changes and future returns. Even when forming portfolios based on breadth changes among retail investors alone, wealth-weighting decreases the spread between the high and low breadth change portfolio returns. The four-factor alpha of the difference between the lowest and highest wealth-weighted retail breadth change portfolios in Panel B is 142 basis points per month (17.0% per year), which is smaller than the 194 basis point per month difference between the lowest and highest equal-weighted retail breadth change portfolios (albeit not significantly so).

When we form portfolios on wealth-weighted breadth changes among institutions only—the measure that places the most emphasis on the large institutions that are probably the most sophisticated investors in the market—the sign of the relationship between breadth changes and future returns flips, reproducing the CHS empirical result: The high wealth-weighted institutional breadth change portfolio significantly outperforms the low wealth-weighted institutional breadth change portfolio by 58, 60, and 67 basis points per month (7.0%, 7.2%, and 8.0% per year) on a raw, one-factor-adjusted, and four-factor-adjusted basis, respectively. Unlike CHS's empirical results, however, the abnormal returns are present only in the high breadth change portfolio (which has a Sharpe ratio of 0.98) and are absent from the low breadth change portfolio. We speculate that the absence of abnormal negative returns in the low breadth change portfolio is due to institutional breadth decreases reflecting not only negative information but also the need to service customer redemptions

The reason wealth-weighted institutional breadth changes are so different from equal-weighted institutional breadth changes is that there are many institutions with extremely small stock portfolios. For example, at the end of May 2007, the median institution in our sample held a stock portfolio worth only about $100,000 which was invested entirely in one stock. Although we do not know the identities of the institutions in our data, we suspect that these small institutional portfolios are held by non-financial companies that do not employ professional portfolio managers and thus behave more like noise traders.

B. Persistence of abnormal returns after portfolio formation

Both retail and institutional breadth changes predict returns, but we document in this subsection that only retail breadth changes significantly predict returns beyond one month into the future.

To assess breadth change's predictive power for returns k months ahead, we sort stocks into quintiles based on their month-end t tradable market capitalization. Within each size quintile, we calculate month t breadth change quintile breakpoints (for total and retail breadth change) or 10th and 90th percentile month t breadth change breakpoints (for institutional breadth change). We calculate each size $\times$ breadth change sub-portfolio's $t + k$ return, weighting stocks by $t + k - 1$ tradable market capitalization. We finally compute the equal-weighted average of the $t + k$ returns of all the highest breadth change sub-portfolios across size quintiles minus the equal-weighted average of the $t + k$ returns of all the lowest breadth change sub-portfolios across size quintiles. Repeating this procedure each calendar month produces a "$t + k$" return spread time series.

Table 3 shows the average return spreads adjusted for size, value, and momentum effects for $k = 2, 3, …, 12$. Equal-weighted retail breadth change significantly predicts returns in every month up to five months into the future. At month $t + 5$, the difference between the highest and lowest breadth change portfolio alphas is still –42 basis points (–5.0% annualized). Even though the alpha differences are no longer significant from months $t + 6$ to $t + 12$, their point estimates are all negative with the exception of month $t + 9$. Wealth-weighted retail breadth change shows a similar amount of predictive persistence; the alpha difference between the highest and lowest wealth-weighted retail breadth change quintiles stops being significant after month $t + 5$, with the exception of a significant negative spread at $t + 10$. Comparing the equal-weighted to the wealth-weighted retail alpha differences at each horizon, we see that from t to $t + 5$, equal-weighted retail breadth change always predicts a larger spread than wealth-weighted retail breadth change, consistent with our $t + 1$ results in Table 2.

In contrast, institutional breadth change does not significantly predict returns beyond one month, whether breadth changes are equal- or wealth-weighted. None of the alpha differences in Table 3 under the institutional columns is significant. However, it is notable that for wealth-weighted institutional breadth change, the alpha difference point estimates are positive in nine out of the eleven time horizons.

As in Table 2, the predictive power of total breadth change beyond the first month is driven by retail investors. The alpha spreads between the highest and lowest equal-weighted total breadth change quintiles are almost the same as those between the highest and lowest equal-weighted retail breadth change quintiles. For portfolios formed on wealth-weighted total breadth

14

change, where institutions have more influence, the alpha spread significance disappears beyond the first month.

C. Subsample tests

In this subsection, we perform our return prediction tests on five subsamples. The first two subsamples are the first half of the sample period (1996-2001) and the second half of the sample period (2002-2007). The third and fourth subsamples restrict portfolios to the smallest and largest size quintiles of stocks. The fifth subsample excludes companies that have issued or repurchased shares in the past twelve months. The motivation for this last exclusion is that stocks may systematically experience breadth increases around share issuances and breadth decreases around share repurchases. In the U.S. market, IPOs and seasoned issues generally have low returns after the issuance date (Ritter (1991), Loughran and Ritter (1995)), and stocks whose companies have repurchased shares have high subsequent returns (Ikenberry, Lakonishok, and Vermaelen (1995)). Therefore, including these stocks in our sample may cause us to confound issuance and repurchase effects with a breadth change effect.

Table 4 shows, for each subsample, the four-factor alpha spread between the highest breadth change and lowest breadth change quantiles in the first month after stocks are sorted by breadth change. The retail breadth change results, whether equal-weighted or wealth-weighted, are robustly present in all subsamples. Unlike many return anomalies documented in the literature, the predictive power of retail breadth change is (insignificantly) stronger among large stocks than small stocks. Excluding recent issuers and repurchasers has no effect on the results. Interestingly, the magnitudes of the retail alpha spreads in the first half of the sample are significantly larger than those in the second half. This could be consistent with increasing sophistication of retail investors over time and/or increasing aggressiveness of institutional investors over time in betting against retail breadth changes, thus attenuating future abnormal returns.

In contrast, the alpha spreads for portfolios formed on institutional breadth change are not significant in some subsamples. Equal-weighted institutional breadth change portfolios continue not to significantly predict returns in all subsamples. Wealth-weighted institutional breadth change generates a significant alpha spread only in the second half of the sample; in the first half, the spread is 45 basis points per month (5.4% per year) but insignificant, whereas in the second

15

half, it is 106 basis points per month (12.7% per year) and highly significant. Wealth-weighted institutional breadth change also significantly predicts returns only among large stocks (alpha spread of 161 basis points per month, or 19.2% per year), not small stocks (insignificant alpha spread of 33 basis points per month, or 4.0% per year). The wealth-weighted institutional breadth change results are not affected, however, by excluding recent issuers and repurchasers. These differences in alphas across subsamples could be due to an increase in sophistication among domestic financial institutions over time, the entry of sophisticated foreign institutions into the SSE in 2003, and the fact that financial institutions tend to focus their attention on large stocks.

IV. Behavior of returns, breadth, and institutional ownership around portfolio formation

In order to better understand the decisions that result in breadth changes and the effect breadth changes might have on prices, we examine in this section the behavior of returns, breadth changes, and institutional ownership percentage in a 48-month window around the breadth change portfolio formation month.

A. Behavior around equal-weighted retail breadth change portfolio formation

The top graph in Figure 1 shows the average excess returns of the lowest, middle, and highest equal-weighted retail breadth change portfolios as a function of months since portfolio formation. Returns on and during the 24 months after the portfolio formation month t are constructed exactly as described in Tables 2 and 3. Returns prior to t are constructed analogously to returns after t. We sort stocks into quintiles based on their month-end t tradable market capitalization. Within each size quintile, we form month t breadth change quintile breakpoints. We calculate each size × breadth change sub-portfolio's $t - j$ return, weighting stocks by $t - j - 1$ tradable market capitalization. Finally, we calculate the $t - j$ return of the "Quintile n portfolio" as the equal-weighted average of the five nth qunitile breadth change sub-portfolio returns, for $j = 1, 2, …, 24.$[15]

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[15] Returns in months prior to t are biased downwards because stocks are sorted into portfolios using future information, month t market capitalization. Stocks with low realized returns from $t - k$ to t tend to be sorted into the small stock quintile and so have high weights at $t - k$ when we value-weight the stocks in this quintile. Similarly, stocks with high realized returns tend to be sorted into the large stock quintile and have low weights. Returns after t do not suffer from this look-ahead bias, so we cannot directly compare returns prior to t to returns afterwards. However, comparisons across different size quintile within a given pre-formation month are informative.

We see in the graph that retail investors tend to start investing in stocks that have had a winning streak during the prior 24 months broken by a low return this month, and they tend to exit stocks with the opposite return pattern.[16] This behavior could be consistent with individuals using a representativeness heuristic (Tversky and Kahneman (1974), Barberis, Shleifer, and Vishny (1998)) to judge that a stock that has had consistently high returns in the past is likely to continue this performance in the future, so an anomalous price dip today represents an attractive buying opportunity because the stock's price will soon bounce back to its previously established trend line. But when many retail investors act upon this belief by buying new positions in a stock, it on average continues to underperform next month and does not outperform subsequently, contrary to the representativeness heuristic prediction. Conversely, a stock that has had consistently low returns in the past is thought to be likely to continue underperforming in the future, so an unusual price increase today creates an attractive temporary exit opportunity for owners of the stock.[17] But when many retail investors respond by completely liquidating their positions, the stock continues to outperform after the portfolio formation month and does not underperform subsequently.

The negative correlation between returns and retail investor breadth change during the portfolio formation month suggests that to the extent retail investors *cause* return continuation after the portfolio formation month, they do so by trading against fundamental news and inhibiting full price reaction during the formation month. The lack of subsequent return reversals is inconsistent with the interpretation that the abnormal portfolio returns after month t are caused by retail-trading-induced price-overshooting. The middle graph of Figure 1 shows that high retail breadth change stocks continue to have significantly elevated retail breadth change in the month following portfolio formation, and a similar pattern holds for low retail breadth change stocks. The positive autocorrelation of retail breadth changes may contribute to the persistence of abnormal returns following the portfolio formation month.

If high retail breadth change stocks typically have large return run-ups prior to the portfolio formation month that are reversed afterwards, do retail investors play a role in the prior

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[16] This pattern is also consistent with previous empirical findings in other countries on retail investor reactions to returns at different horizons (Choe, Kho, and Stulz (1999), Grinblatt and Keloharju (2000, 2001), Benartzi (2001), Goetzmann and Massa (2002), Griffin, Harris, and Topaloglu (2003), Jackson (2003), Richards (2005), Kaniel, Saar, and Titman (2008), Barber, Odean, and Zhu (2009)).

[17] Alternatively, the price rise today might cause some owners' paper losses to become paper gains, causing them to be more eager to liquidate their position at a gain (Shefrin and Statman (1985), Odean (1998)).

run-up? If they do, we might guess that high retail breadth change stocks were overvalued prior to the portfolio formation month, and the formation month is when the bubble begins to burst. Although average returns of high retail breadth change stocks consistently exceed those of low retail breadth change stocks from the second to the 24th month prior to portfolio formation, the former group's retail breadth change consistently lies above the latter's only for the five months immediately prior to the formation month, and the difference is large only for the last two months. In addition, as shown in the bottom graph of Figure 1, average institutional ownership of high retail breadth change stocks is always higher than that of low retail breadth change stocks prior to the formation month, and this ordering reverses during and after the formation month. In sum, there is no strong evidence that retail investors are responsible for the majority of high retail breadth change stocks' run-up prior to portfolio formation.

B. Behavior around wealth-weighted institutional breadth change portfolio formation

Figure 2 contains graphs that are analogous to those in Figure 1, but the series correspond to portfolios formed on wealth-weighted institutional breadth changes, and the middle graph shows wealth-weighted institutional breadth changes instead of equal-weighted retail breadth changes.

In contrast to what we found in Figure 1 with equal-weighted retail breadth changes, the top graph in Figure 2 shows that stocks with high wealth-weighted institutional breadth changes have higher returns than stocks with low wealth-weighted institutional breadth changes in both the portfolio formation month and the first month prior to portfolio formation, but similar returns in the 23 previous months (-24 to -2). Wealth-weighted institutional breadth changes in the formation month represent sharp reversals of the prior ownership trends. Stocks with low wealth-weighted institutional breadth change in month t were experiencing relatively high wealth-weighted institutional breadth changes in the prior seven months (middle graph) and have a higher institutional ownership than high wealth-weighted institutional breadth change stocks during the entire 24 months prior to portfolio formation (bottom graph).

The bottom graph also reveals that stocks in the 10th to 90th percentiles of wealth-weighted institutional breadth change have a substantially lower institutional ownership percentage than stocks in the two extreme deciles. In other words, stocks that do not experience

18

much institutional ownership entry and exit tend to be stocks that are not owned much by institutions at all.[18]

V. Are the breadth change effects just proxies for profitable institutional trades against individuals?

Our results thus far show that when more retail investors hold a stock, its future returns are low, whereas when more institutions hold it, its future returns are high. A natural question then arises: does breadth change capture anything more than the tendency of institutions to profit at the expense of retail investors? We explore this issue using Fama-MacBeth regressions, which allow us to control for more variables than the portfolio-sort approach we used in Section III.

Recall that breadth changes are more volatile among large stocks than small stocks. Therefore, simply pooling all observations in a single Fama-MacBeth regression would cause the breadth coefficients to be identified mostly by the largest stocks. In order to avoid this, we run all the Fama-MacBeth regressions in this paper in the following manner. In each month t, we estimate five separate cross-sectional regressions, one for each tradable market capitalization quintile. The equal-weighted average of that variable's five month t coefficients is that variable's month t coefficient for the overall stock universe. We then apply the usual Fama-MacBeth methodology to the overall coefficient series: the time-series average is the final point estimate of the coefficient, and the time-series standard deviation divided by the square root of the number of months in the sample is the standard error of the coefficient.

The first column of Table 5 shows that when institutions in aggregate increase their holdings of a stock (implying that retail investors have decreased their holdings), the stock performs well in the subsequent month. The coefficients are from a Fama-MacBeth regression where next month's return is predicted by this month's change in the stock's log of institutional ownership percentage, log total market capitalization, book-to-market ratio, and prior-year return excluding the current month. A one standard deviation increase in the log institutional ownership percentage change of a stock predicts a strongly significant increase in its next month's return of $0.333 \times 0.806 = 0.27\%$, or 3.2% on an annualized basis. The second column of Table 5 additionally controls for the current month's stock return, the sum of turnover during the current

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[18] Recall, however, that the sample of stocks used to construct the wealth-weighted institutional breadth change portfolios excludes stocks that have zero institutional ownership in and immediately before the portfolio formation month.

month and prior two months, the Amivest liquidity ratio during the current month, and dummies for the most recent week of trading volume being in the top decile or bottom decile of the last ten weeks. The point estimate on log institutional ownership percentage change barely moves to 0.329, and it remains highly significant.

The third column of Table 5 adds a control for equal-weighted retail breadth change. Equal-weighted retail breadth change is a strong negative predictor of future returns, but institutional ownership change is now significant at only the 10 percent level and has a point estimate of 0.179, which is 55 percent that in the second column. One interpretation of this attenuation is that trading against equal-weighted retail breadth changes accounts for 45% of the profitability of institutional trades against retail investors.

The fourth column of Table 5 adds as an explanatory variable a dummy for a stock being in the top 10 percentiles of wealth-weighted institutional breadth change within its size quintile. We use a dummy instead of a linear control because of the nonlinear effect found in Table 2 (stocks in the highest 10 percentiles of wealth-weighted institutional breadth change earned abnormal returns, whereas those in the lowest 10 percentiles did not). Log institutional ownership percentage change's point estimate attenuates another 51 percent relative to its value in the third column, but being in the top 10 percentiles of wealth-weighted institutional breadth change is a significantly positive predictor of future returns, and equal-weighted retail breadth change continues to be a significantly negative predictor.

Collectively, these results indicate that changes in institutional ownership predict future returns only to the extent that they are correlated with equal-weighted retail breadth changes or wealth-weighted institutional breadth changes. Put another way, breadth changes do not predict returns because they are merely proxies for institutional ownership percentage changes. Rather, institutional ownership percentage changes predict returns because they are proxies for breadth changes. An institution buying shares from an individual positively predicts future returns only if the individual is completely liquidating his position (perhaps signaling something about the depth of the retail population's pessimism) or the institution does not already have shares of this company (indicating that its information is no longer censored by the short-sales constraint).

VI. Is breadth change's predictive power due to investor recognition?

Merton (1987) hypothesizes that when a stock is not widely held because investors are unaware of it, the investors who do hold the stock demand a return premium because they are overweighting it in their portfolios, sacrificing diversification. This return premium is captured by the variable λ, the shadow cost of incomplete information. To test whether the Merton "investor recognition" mechanism is responsible for our breadth change results, we repeat our Fama-MacBeth analysis while directly controlling for λ as operationalized by Bodnaruk and Ostberg (2009) to predict returns in the Swedish stock market.[19]

The penultimate column of Table 5 shows coefficients from a Fama-MacBeth regression where the dependent variable is next month's return and the explanatory variables are λ and the full set of other controls—change in log institutional ownership percentage, equal-weighted retail breadth change, a dummy for being in the top 10 percentiles of wealth-weighted institutional breadth change within the stock's size quintile, log total market capitalization, book-to-market, prior-year return excluding the current month, current month return, prior quarter turnover, liquidity ratio, and dummies for the prior week's volume being in the top decile or bottom decile of the last ten weeks. The coefficient on λ is insignificant and does not have the predicted positive sign, whereas the coefficient on equal-weighted retail breadth change remains negative and strongly significant. The coefficient on the dummy for being in the top 10 percentiles of wealth-weighted institutional breadth change attenuates and is no longer significant, but its standard error is large and the point estimate is not significantly different from its value in the fourth column of Table 5, where we did not control for λ.[20]

We conclude that there is no evidence that λ predicts future returns or is responsible for the ability of equal-weighted retail breadth changes to predict future returns. Wealth-weighted institutional breadth changes are no longer significant once we control for λ, but the fact that λ itself does not predict returns makes this finding difficult to interpret.

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[19] Our tables show results where λ is formed using equal-weighted breadth levels. Using wealth-weighted breadth levels instead gives nearly identical results.

[20] Note, however, that in addition to the difference in explanatory variables, the sample in the fourth column of Table 5 is not the same as the sample in the penultimate column. In order to compute λ, we need a stock to have three years of prior return history, which reduces the sample relative to that in specifications without λ.

VII. Ownership initiations versus discontinuations

In this section, we explore whether ownership initiations have different information content than ownership discontinuations. Recall that by construction, breadth change equals IN (the fraction of investors who initiate ownership) minus OUT (the fraction of investors who discontinue ownership).

The last column of Table 5 shows coefficients from a Fama-MacBeth regression where the dependent variable is next month's return and the explanatory variables are equal-weighted retail IN, equal-weighted retail OUT, wealth-weighted institutional IN, wealth-weighted institutional OUT, and the full set of non-breadth control variables we have in Section V. The estimates show that both components of retail breadth change predict returns, but the coefficient on retail IN is more than twice the coefficient on retail OUT. We speculate that this asymmetry is due to new purchases of a stock being driven by changes in perceived valuation, whereas complete close-outs of positions are often driven by liquidity needs and the disposition effect (Shefrin and Statman, 1985; Odean, 1998) and thus carry less information about general retail beliefs. Neither institutional IN or OUT are significant return predictors, which may be unsurprising given the non-linearity of the institutional breadth change effect in Table 2.

VIII. Conclusion

We have tested the ability of ownership breadth changes to forecast the cross-section of stock returns. Prior theories of the relationship between breadth and future returns make predictions about breadth measured over very specific populations: either the entire investor population in a stock market, or the entire investor population that is unable to short in a stock market. Our key innovation relative to past empirical studies is that we are able to measure breadth over these theoretically relevant populations by using a representative sample of all investors in the Shanghai Stock Exchange, where short-selling is prohibited. We find that the relationship between ownership breadth and future returns depends crucially on the sub-population over which ownership breadth is measured.

Contrary to the Chen, Hong, and Stein (2001) hypothesis that breadth changes measure how much bad news is being withheld from prices due to short-sales constraints, when ownership breadth measured over all investors increases (suggesting a relaxation of short-sales

constraints), future returns are low. This negative relationship is driven by the ownership decisions of small retail investors. Retail investors' ownership breadth changes are negatively correlated with contemporaneous returns, so the negative relationship between total ownership breadth changes and future returns may be caused by contrarian retail trades inhibiting immediate full price adjustment to fundamental news. Abnormal returns persist for five months following portfolio formation, are present in both halves of the sample period, and are equally strong for large and small stocks.

However, the Chen, Hong, and Stein (2001) theory may hold if breadth is measured only over the population of sophisticated investors who observe unbiased signals of a stock's fundamental value. When we restrict our breadth change sample to institutional investors, we find that a large increase in the wealth-weighted number of institutions that hold a stock in a given month predicts a high stock return the following month. However, we do not see corresponding underperformance following a large wealth-weighted decrease in the number of institutional owners. The results on wealth-weighted institutional breadth changes are weaker than the retail breadth change results on other margins as well. Abnormal returns persist for only one month after portfolio formation and are significant only in the second half of the sample period and among large stocks.

Institutional trades against individuals are on average profitable before transactions costs. However, this profitability is almost entirely explained by these trades' correlation with equal-weighted retail breadth changes and wealth-weighted institutional breadth changes. This result indicates that how many shares in aggregate change hands between institutions and individuals does not matter as much as how many of each investor type start and end with holdings of the stock, thus demonstrating the value of disaggregated investor-level data for forecasting future returns.

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Table 1. Summary statistics of variables used in cross-sectional analysis

The cross-sectional means and standard deviations are calculated separately within each month. The table reports the time-series average of these means and standard deviations. Equal-weighted total breadth change is the change between month-ends $t-1$ and t in the number of investors holding stock i divided by the total number of investors. Wealth-weighted total breadth change is like equal-weighted total breadth change, but weights investors by the value of their SSE stock portfolio at the open of month t. Institutional and retail breadth changes are defined analogously on the retail or institutional subsample. Equal-weighted retail IN is the percent of retail investors who held no position in the stock at $t-1$ but held a positive position in it at t. Equal-weighted retail OUT is the percent of retail investors who held a positive position in the stock at $t-1$ but held no position in it at t. Wealth-weighted institutional IN and OUT are defined analogously over institutions, weighting them by their SSE stock portfolio value at the open of month t. Breadth changes, IN, and OUT are expressed as percentages, so that a 1 percent value is coded as 1, rather than 0.01. The variable $\lambda_{i,t}$ is the Merton shadow cost of incomplete information defined in equation (2), and $\Delta\log(\text{Institutional ownership}_{i,t})$ is the change between month-ends $t-1$ and t in the log of the fraction of the stock's tradable A shares held by institutions. $\text{Return}_{i,t-11\to t-1}$ is the stock's cumulative return from month $t-11$ to $t-1$. Liquidity ratio is the sum of the stock's yuan trading volume divided by the sum of the stock's absolute daily returns during month t. High relative volume and low relative volume are dummies for whether the stock's share trading volume during the prior week was in the top tenth or bottom tenth of the ten most recent weeks, respectively. The sample is stock-months where there are a positive number of individual investors and a positive number of institutional investors at both t and $t-1$.

	Mean	Standard deviation
$\text{Return}_{i,\,t+1}$	1.944	9.422
ΔEqual-weighted total breadth$_{i,t}$	-0.002	0.051
ΔEqual-weighted retail breadth$_{i,t}$	-0.002	0.051
Equal-weighted retail IN$_{i,t}$	0.067	0.074
Equal-weighted retail OUT$_{i,t}$	0.069	0.075
ΔEqual-weighted institutional breadth$_{i,t}$	-0.009	0.194
ΔWealth-weighted total breadth$_{i,t}$	-0.031	0.265
ΔWealth-weighted retail breadth$_{i,t}$	-0.025	0.115
ΔWealth-weighted institutional breadth$_{i,t}$	-0.114	2.123
Wealth-weighted institutional IN$_{i,t}$	0.542	1.558
Wealth-weighted institutional OUT$_{i,t}$	0.656	1.684
$\lambda_{i,t}$	0.011	0.039
$\Delta\log(\text{Institutional ownership}_{i,t})$	0.009	0.806
$\log(\text{Total market cap}_{i,t})$	14.562	0.786
Book-to-market$_{i,t}$	0.409	0.193
$\text{Return}_{i,t-11\to t-1}$	17.413	37.316
Prior quarter turnover$_{i,t}$	1.105	0.603
Liquidity ratio$_{i,t}$	0.936	1.387
High relative volume$_{i,t}$	0.124	0.275
Low relative volume$_{i,t}$	0.145	0.271

Table 2. Monthly returns on breadth change portfolios
This table shows the raw return in excess of the riskfree rate, CAPM alpha, and four-factor alpha from portfolios that are formed based on the prior month's equal- or wealth-weighted breadth change among the total, retail, or institutional investor sample. At the end of each month t, we first sort stocks into tradable market capitalization quintiles, and then calculate month t breadth change breakpoints within each size quintile. We value-weight stocks within each market cap × breadth change sub-portfolio. For the total and retail investor samples, to form the "Quintile n" portfolio, we equally weight across the market cap quintiles the five nth quintile breadth change sub-portfolios, and hold the stocks for one month before re-forming the portfolios. The "5 – 1" return is the difference between the Quintile 5 and Quintile 1 portfolio returns. For institutions, to form the "< 10th percentile" portfolio, we equally weight across the size quintiles the five sub-portfolios whose breadth change is less than the 10th percentile and hold the stocks for one month before re-forming the portfolio. The other portfolios are formed in an analogous fashion. The "≥ 90th – < 10th" return is the difference between the "≥ 90th percentile" return and the "< 10th percentile" return. Returns are expressed in percentages, so that a 1 percent return is coded as 1, rather than 0.01. Standard errors are in parentheses.

	Panel A: Total breadth change portfolios					
	Equal-weighted breadth change			Wealth-weighted breadth change		
	Raw return	CAPM alpha	4-factor alpha	Raw return	CAPM alpha	4-factor alpha
Quintile 1	2.87**	1.01**	1.12**	2.18**	0.37	0.52**
(lowest breadth change)	(0.77)	(0.27)	(0.21)	(0.74)	(0.25)	(0.19)
Quintile 2	2.41**	0.49	0.58**	2.16**	0.28	0.35*
	(0.79)	(0.27)	(0.17)	(0.77)	(0.27)	(0.17)
Quintile 3	1.93*	0.13	0.28	1.91*	0.03	0.15
	(0.74)	(0.26)	(0.18)	(0.79)	(0.31)	(0.19)
Quintile 4	1.80*	-0.09	0.04	1.70*	-0.15	-0.03
	(0.78)	(0.27)	(0.19)	(0.77)	(0.28)	(0.19)
Quintile 5	0.84	-1.01**	-0.83**	1.82*	-0.08	0.10
(highest breadth change)	(0.76)	(0.28)	(0.20)	(0.77)	(0.23)	(0.17)
5 – 1	-2.04**	-2.02**	-1.94**	-0.36*	-0.45*	-0.42*
	(0.20)	(0.21)	(0.20)	(0.18)	(0.18)	(0.18)

	Equal-weighted breadth change			Wealth-weighted breadth change		
Panel B: Retail breadth change portfolios						
	Raw return	CAPM alpha	4-factor alpha	Raw return	CAPM alpha	4-factor alpha
Quintile 1 (lowest breadth change)	2.88** (0.77)	1.02** (0.27)	1.13** (0.21)	2.59** (0.76)	0.73** (0.26)	0.88** (0.20)
Quintile 2	2.46** (0.79)	0.52 (0.27)	0.61** (0.17)	2.18** (0.77)	0.31 (0.28)	0.40* (0.17)
Quintile 3	1.91* (0.74)	0.13 (0.26)	0.27 (0.17)	1.93* (0.75)	0.11 (0.28)	0.23 (0.18)
Quintile 4	1.79* (0.77)	-0.08 (0.27)	0.04 (0.19)	1.86* (0.78)	-0.03 (0.27)	0.09 (0.18)
Quintile 5 (highest breadth change)	0.86 (0.77)	-1.00** (0.27)	-0.81** (0.19)	1.19 (0.77)	-0.70** (0.25)	-0.53** (0.17)
5 – 1	-2.03** (0.21)	-2.02** (0.21)	-1.93** (0.21)	-1.39** (0.16)	-1.43** (0.17)	-1.42** (0.17)
Panel C: Institutional breadth change portfolios						
	Raw return	CAPM alpha	4-factor alpha	Raw return	CAPM alpha	4-factor alpha
< 10th percentile	2.35** (0.76)	0.56 (0.32)	0.67* (0.28)	1.92* (0.75)	0.06 (0.22)	0.15 (0.17)
10th to 90th percentiles	1.92* (0.77)	0.04 (0.26)	0.17 (0.16)	1.87* (0.77)	0.00 (0.26)	0.13 (0.17)
≥ 90th percentile	1.92* (0.77)	0.04 (0.25)	0.19 (0.20)	2.51** (0.76)	0.66* (0.26)	0.81** (0.23)
≥ 90th – < 10th	-0.44 (0.31)	-0.52 (0.32)	-0.48 (0.32)	0.58* (0.27)	0.60* (0.28)	0.67** (0.26)

* Significant at the 5% level. ** Significant at the 1% level.

Table 3. Persistence of long-short breadth change portfolio four-factor alphas
This table shows the four-factor alphas from zero-investment portfolios that are formed based on breadth change that is either equal- or wealth-weighted among all, retail, or institutional investors. To form the "Month $t + k$" portfolio, we sort stocks into quintiles based on their month t tradable market capitalization. Then within each size quintile, we calculate month t breadth change quintile breakpoints (for total and retail breadth change) or 10th and 90th percentile month t breadth change breakpoints (for institutional breadth change). We weight stocks by $t + k - 1$ tradable market capitalization within each size $\times$ breadth change sub-portfolio. We then hold long an equal-weighted portfolio of all the highest breadth change sub-portfolios across the size quintiles and short an equal-weighted portfolio of all the lowest breadth change sub-portfolios across size quintiles during month $t + k$ before stocks are re-sorted into (possibly) new portfolios. The number of months used to construct the estimates decreases as k increases due to the boundaries of our sample period. Standard errors are in parentheses.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
Month $t + 2$	-1.02**	-1.00**	0.07	-0.20	-0.65**	0.22
	(0.21)	(0.21)	(0.23)	(0.18)	(0.17)	(0.25)
Month $t + 3$	-0.90**	-0.92**	-0.03	-0.17	-0.64**	0.31
	(0.22)	(0.22)	(0.25)	(0.16)	(0.19)	(0.25)
Month $t + 4$	-0.70**	-0.71**	-0.32	-0.14	-0.40*	0.11
	(0.19)	(0.19)	(0.31)	(0.18)	(0.17)	(0.23)
Month $t + 5$	-0.43*	-0.42*	0.25	-0.30	-0.34*	-0.08
	(0.17)	(0.17)	(0.26)	(0.17)	(0.16)	(0.23)
Month $t + 6$	-0.22	-0.21	0.22	0.08	-0.12	0.22
	(0.20)	(0.20)	(0.23)	(0.16)	(0.15)	(0.23)
Month $t + 7$	-0.14	-0.11	-0.22	0.20	-0.01	0.20
	(0.19)	(0.19)	(0.27)	(0.16)	(0.19)	(0.22)
Month $t + 8$	-0.15	-0.12	0.15	-0.10	-0.15	0.31
	(0.17)	(0.18)	(0.24)	(0.16)	(0.13)	(0.23)
Month $t + 9$	0.09	0.05	0.13	-0.07	-0.21	0.13
	(0.20)	(0.21)	(0.21)	(0.15)	(0.16)	(0.19)
Month $t + 10$	-0.21	-0.18	-0.34	-0.15	-0.30*	-0.19
	(0.19)	(0.18)	(0.27)	(0.15)	(0.14)	(0.22)
Month $t + 11$	-0.08	-0.10	-0.01	0.22	0.01	0.26
	(0.17)	(0.17)	(0.23)	(0.17)	(0.16)	(0.20)
Month $t + 12$	-0.28	-0.30	-0.20	0.11	0.05	0.20
	(0.16)	(0.16)	(0.24)	(0.15)	(0.17)	(0.24)

* Significant at the 5% level. ** Significant at the 1% level.

Table 4. Long-short breadth change portfolio four-factor alphas among subsamples
This table shows the four-factor alphas from zero-investment portfolios that are formed based on breadth change within subsets of our sample: between 1996 and 2001; between 2002 and 2007; within only the smallest tradable market capitalization quintile; within only the largest tradable market capitalization quintile; or excluding stocks for which less than one year has elapsed since a share issuance or repurchase event. Breadth change is either equal- or wealth-weighted among all, retail, or institutional investors. We sort stocks into size quintiles based on their month t tradable market capitalization, and calculate month t breadth change quintile breakpoints (for all and retail investors) or 10th and 90th percentile month t breadth change breakpoints (for institutional investors) within each size quintile. We weight stocks within each size × breadth change sub-portfolio by tradable market capitalization. With the exception of the analyses that include only the smallest or largest size quintile, the portfolios whose alphas we report are long an equal-weighted portfolio of all the highest breadth change sub-portfolios across size quintiles and short an equal-weighted portfolio of all the lowest breadth change sub-portfolios across size quintiles. Stocks are held for one month during $t + 1$ before they are re-sorted into (possibly) new sub-portfolios. Because of months where some size × breadth change subportfolios are empty, the smallest size quintile equal-weighted institutional breadth change returns are calculated using only 133 months, and the largest size quintile equal-weighted institutional breadth change returns are calculated using only 136 months. Standard errors are in parentheses.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
1996-2001	-2.34**	-2.37**	-1.08	-1.17**	-2.02**	0.45
	(0.28)	(0.29)	(0.58)	(0.28)	(0.26)	(0.43)
2002-2007	-1.54**	-1.52**	0.31	0.38*	-0.80**	1.06**
	(0.30)	(0.30)	(0.22)	(0.18)	(0.20)	(0.26)
Smallest size quintile	-1.66**	-1.68**	0.32	-0.41	-0.78*	0.33
	(0.33)	(0.34)	(0.51)	(0.33)	(0.31)	(0.42)
Largest size quintile	-2.04**	-2.03**	-0.26	0.22	-1.45**	1.61**
	(0.44)	(0.43)	(0.54)	(0.38)	(0.35)	(0.58)
No issuances or repurchases in last year	-1.86**	-1.89**	-0.45	-0.44*	-1.26**	0.71*
	(0.24)	(0.24)	(0.29)	(0.20)	(0.20)	(0.29)

* Significant at the 5% level. ** Significant at the 1% level.

Table 5. Future returns: Fama-MacBeth regressions

This table shows coefficients from monthly Fama-MacBeth regressions where the dependent variable is the stock's month $t + 1$ return. Each month, we run cross-sectional regressions separately within each tradable market capitalization quintile and average the coefficients from these five regressions. The coefficients reported in the table are time-series averages of these averaged coefficients, and the standard errors in parentheses are based on the time-series standard deviations of these averaged coefficients. Most of the explanatory variables are as defined in Table 1. "Top 10% of Δwealth-weighted inst. breadth" is a dummy variable for a stock being in the top ten percentiles of month t's wealth-weighted institutional breadth change distribution within its tradable market capitalization quintile. Average R^2 is the average of the cross-sectional regressions' R^2 values. Stock-months are excluded from the sample if there are not a positive number of retail investors and a positive number of institutional investors in the stock at both t and $t - 1$.

Δlog(Institutional Ownership$_{i,t}$)	0.333**	0.329**	0.179	0.087	0.238	0.095
	(0.088)	(0.098)	(0.096)	(0.092)	(0.263)	(0.115)
ΔEqual-weighted retail breadth$_{i,t}$			-39.540**	-37.554**	-35.886**	
			(4.539)	(4.685)	(5.962)	
Top 10% of Δwealth-weighted inst. breadth$_{i,t}$				0.606*	0.003	
				(0.267)	(0.434)	
log(Total market cap$_{i,t}$)	-0.396	-0.266	-0.283	-0.300	-0.348	-0.350
	(0.203)	(0.210)	(0.208)	(0.205)	(0.257)	(0.209)
Book-to-market$_{i,t}$	1.343*	1.566**	1.319*	1.382*	-0.508	1.756**
	(0.575)	(0.555)	(0.548)	(0.548)	(0.999)	(0.536)
Return$_{i,t-11 \to t-1} \div 100$	0.763	1.051*	1.291*	1.267*	2.680*	1.021*
	(0.523)	(0.529)	(0.523)	(0.523)	(1.064)	(0.491)
Return$_{i,t} \div 100$		-1.731	-5.855**	-6.158**	-4.849*	-5.694**
		(1.530)	(1.570)	(1.581)	(2.169)	(1.582)
Prior quarter turnover$_{i,t}$		-0.622**	-0.560*	-0.547*	-0.329	-0.294
		(0.232)	(0.234)	(0.239)	(0.334)	(0.238)
Liquidity ratio$_{i,t}$		-1.934**	-1.898**	-1.910**	-2.921	-1.510*
		(0.635)	(0.631)	(0.673)	(1.701)	(0.748)

High relative volume$_{i,t}$		-0.643**	-0.529*	-0.518*	-0.131	-0.492*
		(0.246)	(0.246)	(0.248)	(0.305)	(0.240)
Low relative volume$_{i,t}$		0.231	0.178	0.189	0.351	0.244
		(0.227)	(0.229)	(0.233)	(0.304)	(0.234)
$\lambda_{i,t}$					-14.384	
					(23.070)	
Equal-weighted retail IN$_{i,t}$						-52.075**
						(6.884)
Equal-weighted retail OUT$_{i,t}$						20.728**
						(6.265)
Wealth-weighted inst. IN$_{i,t}$						-0.456
						(1.832)
Wealth-weighted inst. OUT$_{i,t}$						0.426
						(1.514)
Constant	7.254*	6.911*	7.082*	7.271*	8.635*	8.000*
	(3.227)	(3.262)	(3.260)	(3.218)	(3.828)	(3.295)
# months	137	137	137	137	137	137
Average R^2	0.104	0.211	0.233	0.247	0.363	0.281

* Significant at the 5% level. ** Significant at the 1% level.

Excess returns

Month relative to portfolio formation

Equal-weighted retail breadth change

Month relative to portfolio formation

Institutional ownership percentage

Month relative to portfolio formation

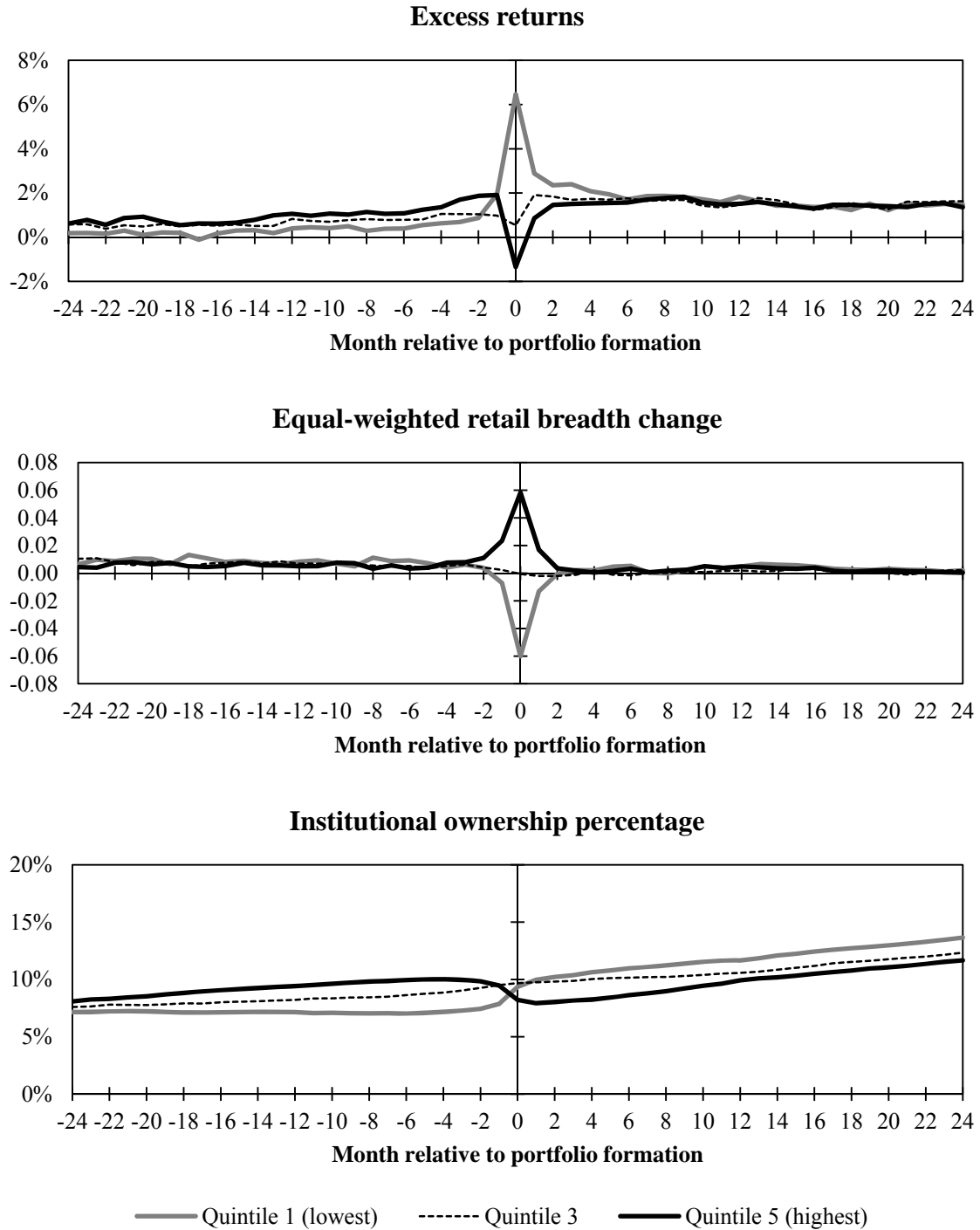——— Quintile 1 (lowest) ------- Quintile 3 ——— Quintile 5 (highest)

Figure 1. Returns, equal-weighted retail breadth change, and institutional ownership in 48-month window around portfolio formation date. The series shown represent statistics on portfolios formed on equal-weighted retail breadth change, as described in Tables 2 and 3.

Excess returns

Month relative to portfolio formation

Wealth-weighted institutional breadth change

Month relative to portfolio formation

Institutional ownership percentage

Month relative to portfolio formation

——— < 10th percentile   ------- 10th-90th percentile   ——— ≥ 90th percentile
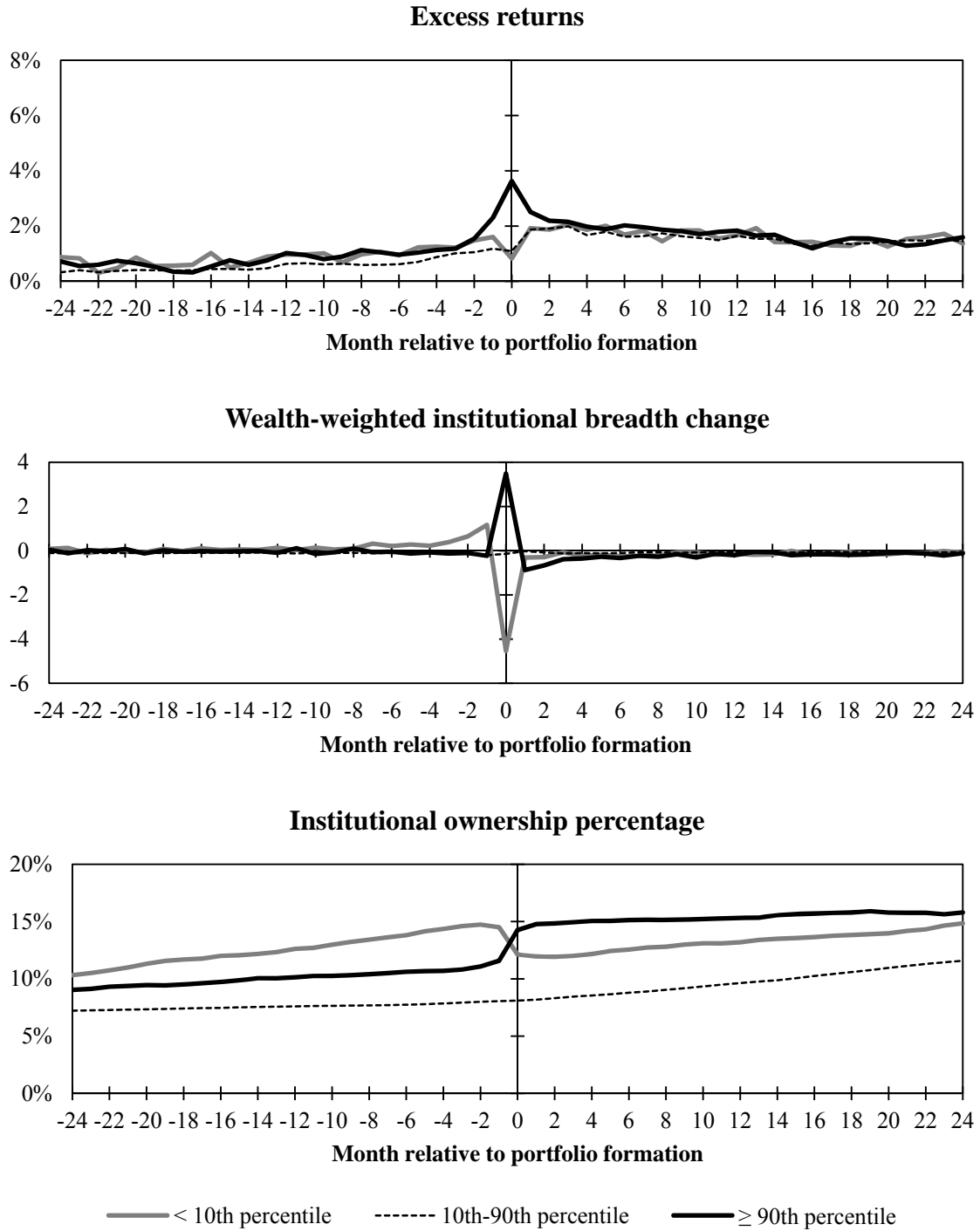
Figure 2. Returns, wealth-weighted institutional breadth change, and institutional ownership in 48-month window around portfolio formation date. The series shown represent portfolios formed on wealth-weighted institutional breadth change, as described in Tables 2 and 3.