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ABSTRACT

Using holdings data on a representative sample of all Shanghai Stock Exchange investors, we show that increases in ownership breadth (the fraction of market participants who own a stock) predict low returns: highest change quintile stocks underperform lowest quintile stocks by 23% per year. Small retail investors drive this result. Retail ownership breadth increases appear to be correlated with overpricing. Among institutional investors, however, the opposite holds: Stocks in the top decile of wealth-weighted institutional breadth change outperform the bottom decile by 8% per year, consistent with prior work that interprets breadth as a measure of short-sales constraints.

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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 in a market with short sales constraints, when an investor holds no long position in a stock, he is likely to have negative information about the stock's fundamental value. Due to short sales constraints, this negative information is only partially incorporated into the stock's price. Thus, when ownership breadth is low, there is a large amount of negative news missing from the stock's price, and the stock's future returns will be low.[1]

Empirically testing this theory is challenging because it requires a representative sample of all investors who face short sales constraints, which is usually not available at high frequency. Previous empirical tests of ownership breadth have measured ownership breadth among U.S. mutual funds, which are not representative of all U.S. investors who face short-sales constraints. 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 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]

[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.

[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.

We use a new holdings dataset from the Shanghai Stock Exchange (SSE) that is uniquely suited to testing the CHS theory. 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, our sample is also representative of all investors in the market who face short-sales constraints.

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 CHS do—the percent of all market participants who have a long position in a stock, giving equal weight to each 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) in the first month after portfolio formation is –23%, 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. (Data on each stock's monthly breadth portfolio assignments are available on the second author's website.)

This finding may be consistent with the lay theory recounted by Lewis (1989): "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." In other words, ownership breadth measures popularity among noise traders who are able to move prices. Indeed, the breadth measure we adopt from CHS is essentially a measure of breadth among retail investors in China, since retail investors vastly outnumber institutions in the market. Portfolios formed on equal-weighted breadth change among only retail investors have returns that are nearly identical to portfolios formed on equal-weighted total breadth change. Lewis is silent on *when* a commodity becomes popular and therefore overvalued. We find that equal-weighted retail breadth change's contemporaneous correlation with a stock's return is negative. Therefore, retail investors may be causing misvaluation by leaning against price movements and delaying full price adjustment to fundamental news.

As we put more weight on sophisticated investors in our breadth measure, the results change. When we redefine total breadth so that investors are weighted by their lagged stock

[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.

market wealth, the annualized four-factor alpha difference between the highest and lowest total breadth change portfolios attenuates to –5% (still statistically significant). Further restricting the population over which we calculation wealth-weighted breadth change to institutions only, we reproduce the original CHS result in a completely new sample: highest-decile wealth-weighted institutional breadth change stocks outperform lowest-decile wealth-weighted institutional breadth change stocks. The annualized difference in the four-factor alphas is 8%, with a *t*-statistic of 2.6.

This last result suggests that when ownership breadth is measured within the population of all sophisticated investors that observe unbiased signals of the stock's fundamental value but cannot short, it functions more in accordance with the CHS theory, primarily reflecting how much negative information is not in the stock price due to short-sales constraints. The CHS model does not have unsophisticated traders who observe no fundamental signals, which could be why it no longer applies once ownership breadth is measured over a population of predominantly unsophisticated retail investors.

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% higher on an annualized basis. But the significance of institutional ownership percentage changes disappears once we control for equal-weighted retail breadth changes and wealth-weighted institutional breadth changes, while both breadth change measures remain significant return predictors. In other words, an institution buying shares from an individual positively predicts future returns only if the individual is completely liquidating his position or the institution previously had no position in the stock. 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 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 main 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 on investor sentiment measures,[5] and research on the portfolio performance of institutional versus individual investors.[6]

The remainder of the paper is organized as follows. Section I describes our data, and 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

[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] Examples include Lee, Shleifer, and Thaler (1991), Baker and Wurgler (2006, 2007), Cornelli, Goldreich, and Ljunqvist (2006), Kumar and Lee (2006), Qiu and Welch (2006), Tetlock (2007), Da, Engelberg, and Gao (2011), Hwang (2011), Baker, Wurgler, and Yuan (2012), and Ben-Rephael, Kandel, and Wohl (2012).

[6] See, for example, Gruber (1996), Daniel, Grinblatt, Titman, and Wermers (1997), Zheng (1999), Chen, Jegadeesh, and Wermers (2000), Seasholes and Wu (2007), Frazzini and Lamont (2008), Kaniel, Saar, and Titman (2008), Barber, Lee, Liu, and Odean (2008), Campbell, Ramadorai, and Schwartz (2009), Kelley and Tetlock (2010), and Barber, Odean, and Zhu (forthcoming).

and why breadth changes might be related to future returns. Section V explores the relationship between breadth changes and changes in institutional ownership percentages. Section VI compares the return-predicting ability of retail breadth changes in months with and without earnings announcements to assess whether breadth changes reflect anything more than trading by investors with private information. Section VII investigates the extent to which breadth changes predict future returns via a Merton (1987) investor recognition channel, and Section VIII discusses the different implications that ownership initiations versus discontinuations have for future returns. Section IX 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. Mainland 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.

Almost all SSE shares are A shares, which only domestic investors could hold until 2003. At year-end 2007, A shares constituted over 99% of SSE market capitalization. B shares are quoted in U.S. dollars and can be held by foreign and (since 2001) domestic investors. Shares are further classified into tradable and non-tradable shares. 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").[7] We use the term "tradable market capitalization" to refer to the value of tradable A shares, and "total market capitalization" to refer to the combined

[7] Beginning in April 2005, non-tradable shares began to be converted to tradable status, although the conversion process was slow enough that as of year-end 2007, 72% of total Chinese market capitalization remained non-tradable. Converted tradable shares were subject to a one-year lockup, and investors holding more than a 5% 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 5, except that in the shorter sample, the long-short wealth-weighted total breadth change portfolio's three-factor alpha is significant at the 1% level, and the long-short wealth-weighted institutional breadth change portfolio's one-factor alpha is significant at the 10% level and the four-factor alpha is significant at the 5% level.

value of tradable and non-tradable A shares. During our sample period, about 27% of SSE market capitalization was tradable.

To trade on the SSE, both retail and institutional investors are required to open an account with the Exchange, at which point they must identify themselves to the Exchange as an individual or an institution. 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 A-share 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. 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.

Table 1 shows the mean and median value in RMB of an investor's holdings in a single company, conditional on investing in the company, as well as the mean and median value of an investor's total stock portfolio. For most of the sample period, the exchange rate was about 8.3 RMB per U.S. dollar, but it then fell to 7.7 RMB per U.S. dollar from July 2005 to May 2007. Retail investors start with a mean (median) stock position value of 8,069 (3,900) RMB and a mean (median) total portfolio value of 22,179 (8,680) RMB in 1996. By 2007, the last year of our sample, these values have increased to 21,992 (6,670) RMB and 54,759 (13,620) RMB, respectively. Even adjusting for the 16% rise in the Chinese consumer price index over this period, this represents a sizable increase in the position and portfolio values of retail investors. Institutions start with a mean (median) stock position value of 738,976 (54,375) RMB, and a

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

mean (median) total portfolio value of 3,572,650 (198,102) RMB in 1996. Their mean (median) stock position value increased to 8,153,493 (185,187) RMB and their total portfolio value increased to 32,808,349 (330,980) RMB by 2007. Institutional investors' portfolio values grew much more quickly than retail investors', particularly for the means. The median institutional investor portfolio is strikingly small throughout the sample period—far less than 100,000 USD—and the large difference between the mean and the median values indicates that the portfolio value distribution is extremely right-skewed.

We obtain stock return, market capitalization, earnings announcement date, 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 as follows. 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 one investor partially liquidates her position in the stock to sell to one or more investors who previously did not own the stock, or one investor completely liquidates her position by selling her shares to two or more

[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.

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.

To assess the extent to which unsophisticated investors drive the negative correlation between total ownership breadth change and future returns, we use an alternative measure of ownership breadth not found in CHS that de-emphasizes small investors by weighting investors by the value of their SSE portfolio at the beginning of the month.[10] 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

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

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.

[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.

Our main cross-sectional analysis involves evaluating the return performance of portfolios formed on breadth changes. We estimate one, three, and 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 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

[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.

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 higher expected return. Investor recognition is closely related to ownership breadth changes, so it is important to explore the extent to which breadth changes predict returns through the investor recognition channel. 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 2 displays 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.

Table 3 shows the mean and standard deviation of breadth changes separately for each year of our sample. The mean equal-weighted breadth changes are close to zero in every year; the largest magnitude occurs in 1996, when the mean equal-weighted institutional breadth change takes on a value of only –0.069%. The average wealth-weighted breadth changes experience considerably more variation, particularly among institutions. The average wealth-weighted institutional breadth change experiences two valleys of –0.446% and –0.525% in 1996 and 2003, respectively. The cross-sectional standard deviation of breadth changes generally falls as the sample period progresses, with the exception of institutional wealth-weighted breadth changes, which exhibits its greatest dispersion from 1998 to 2000, and total wealth-weighted breadth changes, whose dispersion follows a U-shaped path with respect to time.

Table 4 contains the correlations among the various breadth measures. Equal-weighted total and retail breadth changes are almost perfectly positively correlated with each other. Equal-weighted institutional breadth changes are mildly positively correlated (0.054) with equal-weighted retail breadth changes. Wealth-weighted retail breadth changes are strongly positively correlated with equal-weighted retail breadth changes, but the correlation coefficient of 0.643 indicates that there is still considerable divergence between these two retail breadth change measures. Wealth-weighted institutional breadth change is negatively correlated with retail breadth change, and this negative correlation is stronger with equal-weighted retail breadth change (–0.117) than with wealth-weighted retail breadth change (–0.030). Wealth-weighted institutional breadth change exhibits only some positive correlation (0.305) with equal-weighted institutional breadth change, showing that large institutions behave differently from small institutions.

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 five groups based on tradable market capitalization (0th to 20th size percentile, 20th percentile to 40th size percentile, …, 80th percentile to 100th size percentile). Within each size quintile, we form five sub-portfolios based on breadth change during *t*, creating a total of 25 sub-portfolios. The breadth change breakpoints that determine the sub-portfolio boundaries differ by size quintile, so that all 25 sub-portfolios contain the same number of stocks. We weight stocks by tradable market capitalization within each sub-portfolio. To form the "Quintile *n*" breadth change portfolio, we equally weight across size quintiles the five *n*th quintile breadth change sub-portfolios, and hold the stocks for one month before re-forming the portfolios at the end of month t + 1. We adopt this sequential sorting methodology because the volatility of breadth change increases with firm size. If we sorted stocks by breadth change without considering size, very few small firms would be in the extreme quintiles of breadth change.

Table 5 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 when we adjust the return using the CAPM, three-factor, and four-factor models: It is 202 basis points per month (24.2% per year) with a *t*-statistic of 9.6 when we adjust for CAPM beta risk, 197 basis points per month (23.6% per year) with a *t*-statistic of 9.4 when we additionally adjust for size and value effects, and 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.[13] The remainder of this subsection shows that ownership breadth among small, unsophisticated investors is responsible for the rejection of the CHS prediction.

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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

In the right half of Table 5's Panel A, we see that when we use wealth-weighted total breadth changes to form portfolios, the raw return difference between the lowest and highest breadth change quintiles falls 82% to 36 basis points per month (4.3% per year), although this difference remains significant at the 5% level. Adjusting the difference by the one-factor, three-factor, or four-factor model yields slightly larger and still-significant alphas: 45 basis points, 41 basis points, and 42 basis points per month (5.4%, 4.9%, and 5.0% per year), respectively.

Further evidence on the role of unsophisticated investors comes from Panels B and C of Table 5, 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]

We 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.[15] As we have

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.

[14] Out of 137 × 3 × 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.

[15] It is believed that Chinese mutual fund managers sometimes front-run their own fund's trades by trading in retail accounts (Ren (2011)). This practice is known by the colorful name of "rat trading" and could raise the concern that employees of institutional investors are responsible for much of the retail trading we observe. However, we find that retail breadth increases lead to lower subsequent returns, which suggests that front-running is not a major determinant of retail breadth changes in our data. It is also believed that some institutions used individual IDs to open a large number of accounts, which are dubbed "gunny sack accounts," mostly in order to increase the institution's allocation of underpriced IPO shares, since there is a quota for the maximum allocation to each account. This practice is thought to have gradually disappeared since 2002, when the Chinese Securities Regulatory Commission tightened its oversight. There were also anecdotal cases of institutions using these accounts to manipulate stock prices (e.g., Zhou (2005)). Our retail breadth findings are not driven by IPO-related trading, since we obtain similar results after excluding newly issued stocks. Our findings are also not likely to be due to price manipulation with gunny sack accounts. If retail breadth changes were primarily driven by institutions using

previously noted, 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 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 alphas of the difference between the lowest and highest wealth-weighted retail breadth change portfolios in Panel B are between 142 and 143 basis points per month (17.0% to 17.1% per year), which is smaller than the 193 to 202 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, 71, and 67 basis points per month (7.0%, 7.2%, 8.5%, and 8.0% per year) on a raw, one-factor-adjusted, three-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 large difference between wealth-weighted and equal-weighted institutional breadth changes is not necessarily surprising in light of the fact that there are many institutions with extremely small stock portfolios. Recall that the median institution in our sample holds a stock portfolio worth less than 100,000 U.S. dollars. The median number of stocks held by an institution in May 2007 is one. Although we do not know the identities of the institutions in our

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individual accounts in pump-and-dump schemes, retail breadth changes should be positively correlated with contemporaneous returns—the opposite of what we find.

data, we suspect that these small institutional portfolios are held by non-financial companies that do not employ professional portfolio managers and thus trade like unsophisticated investors.

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. This difference in persistence is evidence that retail breadth changes do not predict returns merely because they are negatively correlated with institutional breadth changes. (We will formally test the independent ability of retail versus institutional breadth changes to predict returns in the Fama-MacBeth analysis in Section V.)

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 form 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 × 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 6 shows the one, three, and four-factor alphas of return spreads for $k = 2, 3, \ldots, 12$. For brevity, we will discuss only the four-factor alphas, although the other alpha results are quite similar. 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 four-factor alphas is still –42 basis points (–5.0% annualized). Even though the four-factor 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 four-factor 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 four-factor 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 5.

In contrast, institutional breadth change does not significantly predict returns beyond one month, whether breadth changes are equal- or wealth-weighted. None of the four-factor alpha differences in Table 6 under the institutional columns is significant. However, it is notable that for wealth-weighted institutional breadth change, the four-factor alpha difference point estimates are positive in nine out of the eleven time horizons.

As in Table 5, the predictive power of total breadth change beyond the first month is driven by retail investors. The four-factor 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 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 7 shows, for each subsample, the one, three, and four-factor alpha spreads 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 four-factor alpha spreads in the first half of the sample are significantly larger[16] 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 every subsample except when restricting to the 1996 to 2001 period, when its one and three-factor alphas are negative and significant. Wealth-weighted institutional breadth change generates a significant alpha spread only in the second half of the sample; in the first half, the four-factor spread is 45 basis points per month (5.4% per year) but insignificant, whereas in the second 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 (four-factor alpha spread of 161 basis points per month, or 19.2% per year), not small stocks (insignificant four-factor 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 why breadth changes might affect 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.

[16] The differences are significant at the 5% level or greater, except for the three-factor equal-weighted retail alphas, which are significantly different at the 10% level.

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 5 and 6. 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 quintile breadth change sub-portfolio returns, for $j = 1, 2, \ldots, 24$.[17]

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.[18] 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

[17] 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.

[18] 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)).

owners of the stock.[19] 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 retail breadth does not predict future returns due to pump-and-dump schemes where institutions artificially push up prices in order to attract trend-chasing retail investors before selling at a profit. The negative correlation also suggests that if retail investors cause return continuation, 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 abnormal portfolio returns after month t being 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, could retail investors play a role in the prior 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.

[19] 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)).

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 during the entire 24 months prior to portfolio formation than stocks with high wealth-weighted institutional breadth change in month t (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 much institutional ownership entry and exit tend to be stocks that are not owned much by institutions at all.[20]

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.

[20] 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.

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 8 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 8 additionally controls for the current month's stock return, the sum of turnover during the current 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 8 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% level and has a point estimate of 0.179, which is 55% 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 8 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 5 (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% relative to its value in the third column and is not significant even at the 10% level, 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 percentage 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. Does retail breadth change predict returns only because it is correlated with informed trading?

It is possible that retail breadth changes predict future returns not because retail investors push prices away from fundamentals, but because small retail investors are disproportionately likely to be counterparties to informed traders. Abnormal returns could then occur when these informed traders' private information becomes public after the portfolio formation month. In this section, we provide some evidence that this channel is unlikely to account for all the predictive power of retail breadth changes.

If abnormal returns of portfolios formed on retail breadth changes are solely the result of private information becoming public after the portfolio formation date, then a retail breadth change in a month where the firm has made an earnings announcement should be less predictive of the next month's returns. This is because the earnings announcement made public much of the private information that informed investors were trading on during the announcement month, leaving less of this private information to be revealed in the following month.[21] We therefore test whether retail breadth changes are less predictive of returns that occur in the month after an earnings announcement.

From 1996 to 2001, Chinese companies released earnings twice a year. Starting in 2002, earnings were released quarterly. Six calendar months—February, March, April, July, August, and October—collectively contain 99.75% of the earnings announcements between 1996 and 2007. Using equal-weighted retail breadth changes in these six months to construct portfolios, we find that the average four-factor alpha difference between the highest and lowest breadth change portfolios in the following month, when relatively less private information should be revealed, is –1.98% (*s.e.* = 0.29, t = 6.83). In the other six months, the average four-factor alpha spread is –1.72% (*s.e.* = 0.31, t = 5.55). These two alpha spreads are not statistically distinguishable from each other, and the larger magnitude of the alpha spread point estimate in the months following an earnings release is the opposite of what the informed-trading-only story would predict.

Because not all firms announce earnings in the same month, we can also use within-month variation to identify whether equal-weighted retail breadth changes are less predictive of returns when the breadth changes occur in an earnings announcement month. The fifth column of Table 8 shows coefficients from a Fama-MacBeth return prediction regression where we control for all the variables we used in Section V, a dummy for whether the company announced earnings in that month, and interactions of that dummy with equal-weighted retail breadth change and a dummy for wealth-weighted institutional breadth change being in the top 10 percentiles within the stock's size quintile. In order to avoid identifying these additional coefficients from only a tiny number of announcing companies, we restrict the sample to months when at least 100 firms in the Fama-MacBeth sample announced earnings and some firms did not announce earnings, which reduces the number of months in the regression from 137 to 34. The interaction between equal-weighted retail breadth change and the earnings announcement dummy is not significant, and its point estimate is negative, indicating that if anything, equal-weighted retail breadth change is *more* predictive of future negative returns when breadth change is measured in an earnings-announcement month.

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[21] See Tetlock (2010) for evidence that public financial announcements reduce the amount of asymmetric information about a company.

In sum, both across-month and within-month comparisons indicate that equal-weighted retail breadth change is not less predictive of returns that occur when relatively little private information is revealed. If anything, the relationship is the opposite. This suggests that the abnormal returns of portfolios formed using retail breadth change are not entirely due to retail breadth changes being negatively correlated with the trading flow of informed investors whose private information is subsequently revealed.

VII. 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.[22]

The penultimate column of Table 8 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 from Section V. 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 8, where we did not control for λ.[23]

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.

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

[23] Note, however, that in addition to the difference in explanatory variables, the sample in the fourth column of Table 8 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.

VIII. 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 8 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 from Section V. The estimates show that the coefficient magnitude on retail IN is more than twice the coefficient magnitude on retail OUT, but both components of retail breadth change significantly predict returns. The fact that retail OUT predicts returns is additional evidence against the investor recognition hypothesis being responsible for the ability of retail ownership breadth to predict returns, since investors who have just liquidated their holdings of a stock are presumably aware of its existence. 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 5.

IX. Conclusion

We have tested the ability of ownership breadth changes to forecast the cross-section of stock returns. The prior theory on the relationship between breadth and future returns makes predictions about breadth measured over a very specific population: all investors in a stock market who face short-sales constraints. Our key innovation relative to past empirical studies is that we are able to measure breadth over this theoretically relevant population 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. The negative relationship between total ownership breadth changes and future returns is consistent with contrarian retail trades inhibiting immediate full price adjustment to fundamental news. Breadth behaves more in accordance with the Chen, Hong, and Stein (2001) theory if it is measured only over a population of sophisticated 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.

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. Portfolio and position summary statistics

This table reports (in RMB), separately for retail and institutional investors at the beginning of each year in our sample, the mean and median of investors' individual stock position values and the mean and median of investors' total stock portfolio value.

	Retail investors				Institutional investors			
	Individual position value		Total portfolio value		Individual position value		Total portfolio value	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1996	8,069	3,900	22,179	8,680	738,976	54,375	3,572,650	198,102
1997	11,091	5,680	28,735	12,375	802,767	47,880	2,921,252	119,175
1998	11,241	5,696	30,802	13,313	1,090,328	42,205	3,788,510	86,440
1999	12,536	6,100	33,955	14,177	2,400,134	40,358	8,294,886	102,264
2000	16,879	7,920	43,468	17,908	3,114,389	36,960	9,977,062	118,080
2001	17,528	8,477	46,671	19,895	2,389,368	34,700	8,211,759	133,313
2002	15,047	7,220	40,557	17,159	2,026,537	45,570	8,309,475	184,118
2003	13,768	6,349	37,537	15,025	2,320,780	37,400	9,515,146	216,850
2004	14,040	6,040	38,423	14,360	3,242,438	55,680	13,177,925	286,178
2005	11,261	4,308	30,463	10,390	4,107,368	54,810	16,793,688	203,138
2006	17,915	5,627	46,182	13,172	7,195,547	134,456	26,866,712	288,191
2007	21,992	6,670	54,759	13,620	8,153,493	185,187	32,808,349	330,908

Table 2. 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 Δlog(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. Return$_{i,t-11\rightarrow t-1}$ 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
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
Δlog(Institutional ownership$_{i,t}$)	0.009	0.806
log(Total market cap$_{i,t}$)	14.562	0.786
Book-to-market$_{i,t}$	0.409	0.193
Return$_{i,t-11\rightarrow t-1}$	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 3. Mean and standard deviation of breadth change in each year

This table shows the cross-sectional mean and standard deviation (in parentheses below the mean) of the six kinds of breadth change within each year. The means and standard deviations are calculated separately within each month, and we report the time-series average of these means and standard deviations within each year.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
1996	-0.009	-0.009	-0.069	-0.126	-0.111	-0.446
	(0.177)	(0.177)	(0.486)	(0.455)	(0.461)	(2.505)
1997	0.014	0.014	-0.020	-0.034	-0.033	-0.005
	(0.113)	(0.113)	(0.296)	(0.221)	(0.224)	(1.508)
1998	0.000	0.000	-0.016	-0.027	-0.025	-0.147
	(0.069)	(0.069)	(0.200)	(0.198)	(0.133)	(4.509)
1999	-0.002	-0.002	-0.013	-0.033	-0.025	-0.167
	(0.054)	(0.054)	(0.159)	(0.295)	(0.097)	(5.160)
2000	0.001	0.001	-0.015	-0.035	-0.023	-0.175
	(0.069)	(0.069)	(0.188)	(0.295)	(0.106)	(3.884)
2001	0.002	0.002	-0.012	-0.024	-0.010	-0.211
	(0.025)	(0.025)	(0.130)	(0.168)	(0.044)	(2.503)
2002	-0.001	-0.001	-0.003	-0.026	-0.008	-0.158
	(0.014)	(0.014)	(0.129)	(0.214)	(0.035)	(2.536)
2003	-0.001	-0.001	-0.013	-0.070	-0.010	-0.525
	(0.018)	(0.018)	(0.207)	(0.286)	(0.061)	(2.246)
2004	0.000	0.000	-0.005	-0.020	-0.009	-0.067
	(0.020)	(0.020)	(0.222)	(0.286)	(0.051)	(1.607)
2005	-0.001	-0.001	-0.003	0.000	-0.005	0.009
	(0.012)	(0.012)	(0.192)	(0.329)	(0.054)	(1.291)
2006	-0.002	-0.002	-0.005	-0.017	-0.016	-0.014
	(0.034)	(0.034)	(0.220)	(0.450)	(0.104)	(1.452)
2007	0.004	0.004	0.003	-0.017	-0.024	0.000
	(0.068)	(0.068)	(0.148)	(0.569)	(0.112)	(1.474)

Table 4. Correlation of breadth change measures with each other

Each month, we calculate the cross-sectional correlation of each breadth measure with the other breadth measures. The table reports the time-series mean of these correlations, with the standard error (computed as the time-series standard deviation of the correlation divided by the square root of the number of months) in parentheses below.

		Equal-weighted breadth change			Wealth-weighted breadth change		
		Total	Retail	Inst.	Total	Retail	Inst.
Equal-weighted breadth change	Total	1.000**	1.000**	0.058**	0.128**	0.643**	-0.117**
		(0.000)	(0.000)	(0.016)	(0.028)	(0.015)	(0.015)
	Retail		1.000**	0.054**	0.127**	0.643**	-0.117**
			(0.000)	(0.016)	(0.028)	(0.015)	(0.015)
	Inst.			1.000**	0.294**	0.141**	0.305**
				(0.000)	(0.014)	(0.016)	(0.013)
Wealth-weighted breadth change	Total				1.000**	0.347**	0.811**
					(0.000)	(0.032)	(0.026)
	Retail					1.000**	-0.030*
						(0.000)	(0.012)
	Inst.						1.000**
							(0.000)

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

Table 5. Monthly returns on breadth change portfolios

This table shows the raw return in excess of the riskfree rate and one, three, and four-factor alphas 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 *n*th 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	3-factor alpha	4-factor alpha	Raw return	CAPM alpha	3-factor alpha	4-factor alpha
Quintile 1	2.87**	1.01**	1.10**	1.12**	2.18**	0.37	0.49*	0.52**
(lowest breadth change)	(0.77)	(0.27)	(0.21)	(0.21)	(0.74)	(0.25)	(0.20)	(0.19)
Quintile 2	2.41**	0.49	0.54**	0.58**	2.16**	0.28	0.32	0.35*
	(0.79)	(0.27)	(0.19)	(0.17)	(0.77)	(0.27)	(0.19)	(0.17)
Quintile 3	1.93*	0.13	0.26	0.28	1.91*	0.03	0.11	0.15
	(0.74)	(0.26)	(0.18)	(0.18)	(0.79)	(0.31)	(0.21)	(0.19)
Quintile 4	1.80*	-0.09	0.00	0.04	1.70*	-0.15	-0.06	-0.03
	(0.78)	(0.27)	(0.21)	(0.19)	(0.77)	(0.28)	(0.20)	(0.19)
Quintile 5	0.84	-1.01**	-0.87**	-0.83**	1.82*	-0.08	0.08	0.10
(highest breadth change)	(0.76)	(0.28)	(0.22)	(0.20)	(0.77)	(0.23)	(0.18)	(0.17)
5 – 1	-2.04**	-2.02**	-1.97**	-1.94**	-0.36*	-0.45*	-0.41*	-0.42*
	(0.20)	(0.21)	(0.21)	(0.20)	(0.18)	(0.18)	(0.18)	(0.18)

Panel B: Retail breadth change portfolios								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	Raw return	CAPM alpha	3-factor alpha	4-factor alpha	Raw return	CAPM alpha	3-factor alpha	4-factor alpha
Quintile 1	2.88**	1.02**	1.11**	1.13**	2.59**	0.73**	0.86**	0.88**
(lowest breadth change)	(0.77)	(0.27)	(0.21)	(0.21)	(0.76)	(0.26)	(0.21)	(0.20)
Quintile 2	2.46**	0.52	0.57**	0.61**	2.18**	0.31	0.36	0.40*
	(0.79)	(0.27)	(0.19)	(0.17)	(0.77)	(0.28)	(0.19)	(0.17)
Quintile 3	1.91*	0.13	0.25	0.27	1.93*	0.11	0.20	0.23
	(0.74)	(0.26)	(0.18)	(0.17)	(0.75)	(0.28)	(0.19)	(0.18)
Quintile 4	1.79*	-0.08	-0.00	0.04	1.86*	-0.03	0.06	0.09
	(0.77)	(0.27)	(0.21)	(0.19)	(0.78)	(0.27)	(0.19)	(0.18)
Quintile 5	0.86	-1.00**	-0.85**	-0.81**	1.19	-0.70**	-0.57**	-0.53**
(highest breadth change)	(0.77)	(0.27)	(0.22)	(0.19)	(0.77)	(0.25)	(0.19)	(0.17)
5 – 1	-2.03**	-2.02**	-1.96**	-1.93**	-1.39**	-1.43**	-1.43**	-1.42**
	(0.21)	(0.21)	(0.21)	(0.21)	(0.16)	(0.17)	(0.17)	(0.17)

Panel C: Institutional breadth change portfolios								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	Raw return	CAPM alpha	3-factor alpha	4-factor alpha	Raw return	CAPM alpha	3-factor alpha	4-factor alpha
< 10th	2.35**	0.56	0.63*	0.67*	1.92*	0.06	0.12	0.15
percentile	(0.76)	(0.32)	(0.29)	(0.28)	(0.75)	(0.22)	(0.18)	(0.17)
10th to 90th	1.92*	0.04	0.13	0.17	1.87*	0.00	0.09	0.13
percentiles	(0.77)	(0.26)	(0.18)	(0.16)	(0.77)	(0.26)	(0.18)	(0.17)
≥ 90th	1.92*	0.04	0.18	0.19	2.51**	0.66*	0.83**	0.81**
percentile	(0.77)	(0.25)	(0.20)	(0.20)	(0.76)	(0.26)	(0.23)	(0.23)
≥ 90th – < 10th	-0.44	-0.52	-0.45	-0.48	0.58*	0.60*	0.71*	0.67**
	(0.31)	(0.32)	(0.32)	(0.32)	(0.27)	(0.28)	(0.27)	(0.26)

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

Table 6. Persistence of long-short breadth change portfolio alphas

This table shows the one, three, and 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 × 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.

Panel A: One-factor alphas

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
Month t + 2	-0.95**	-0.93**	0.13	-0.12	-0.58**	0.20
	(0.21)	(0.21)	(0.23)	(0.18)	(0.17)	(0.25)
Month t + 3	-0.93**	-0.94**	0.02	-0.21	-0.61**	0.15
	(0.22)	(0.22)	(0.24)	(0.16)	(0.19)	(0.26)
Month t + 4	-0.63**	-0.63**	-0.45	-0.02	-0.35	0.14
	(0.20)	(0.20)	(0.31)	(0.19)	(0.18)	(0.22)
Month t + 5	-0.42*	-0.41*	0.14	-0.33*	-0.38*	-0.11
	(0.18)	(0.18)	(0.27)	(0.16)	(0.17)	(0.23)
Month t + 6	-0.27	-0.26	0.25	0.09	-0.13	0.22
	(0.20)	(0.20)	(0.23)	(0.16)	(0.16)	(0.24)
Month t + 7	-0.19	-0.19	-0.35	0.12	-0.13	0.09
	(0.20)	(0.21)	(0.27)	(0.16)	(0.20)	(0.23)
Month t + 8	-0.21	-0.20	0.25	-0.06	-0.13	0.43
	(0.18)	(0.18)	(0.24)	(0.16)	(0.13)	(0.24)
Month t + 9	-0.01	-0.05	-0.00	-0.18	-0.25	0.04
	(0.22)	(0.22)	(0.23)	(0.17)	(0.17)	(0.19)
Month t + 10	-0.19	-0.18	-0.39	-0.16	-0.29*	-0.20
	(0.19)	(0.18)	(0.26)	(0.16)	(0.14)	(0.22)
Month t + 11	-0.09	-0.11	-0.10	0.18	-0.01	0.17
	(0.18)	(0.18)	(0.23)	(0.17)	(0.15)	(0.20)
Month t + 12	-0.33*	-0.35*	-0.15	0.03	0.03	0.17
	(0.16)	(0.16)	(0.23)	(0.14)	(0.17)	(0.23)

Panel B: Three-factor alphas						
	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
Month *t* + 2	-1.03**	-1.01**	0.09	-0.20	-0.65**	0.22
	(0.21)	(0.21)	(0.23)	(0.18)	(0.17)	(0.25)
Month *t* + 3	-0.93**	-0.94**	-0.04	-0.17	-0.63**	0.30
	(0.22)	(0.22)	(0.25)	(0.16)	(0.19)	(0.25)
Month *t* + 4	-0.69**	-0.70**	-0.33	-0.12	-0.40*	0.13
	(0.19)	(0.19)	(0.31)	(0.19)	(0.17)	(0.23)
Month *t* + 5	-0.47*	-0.46*	0.25	-0.31	-0.38*	-0.08
	(0.18)	(0.18)	(0.26)	(0.17)	(0.17)	(0.23)
Month *t* + 6	-0.26	-0.24	0.23	0.11	-0.14	0.26
	(0.20)	(0.20)	(0.23)	(0.16)	(0.16)	(0.24)
Month *t* + 7	-0.20	-0.18	-0.25	0.20	-0.06	0.21
	(0.21)	(0.21)	(0.27)	(0.16)	(0.20)	(0.22)
Month *t* + 8	-0.18	-0.15	0.19	-0.08	-0.14	0.35
	(0.18)	(0.18)	(0.24)	(0.16)	(0.13)	(0.24)
Month *t* + 9	0.06	0.01	0.11	-0.10	-0.24	0.11
	(0.21)	(0.21)	(0.21)	(0.16)	(0.16)	(0.19)
Month *t* + 10	-0.20	-0.17	-0.34	-0.12	-0.28*	-0.15
	(0.19)	(0.18)	(0.26)	(0.16)	(0.14)	(0.22)
Month *t* + 11	-0.11	-0.14	-0.06	0.22	-0.00	0.26
	(0.18)	(0.18)	(0.23)	(0.17)	(0.16)	(0.19)
Month *t* + 12	-0.30	-0.32*	-0.15	0.07	0.02	0.17
	(0.16)	(0.16)	(0.24)	(0.14)	(0.17)	(0.23)

Panel C: Four-factor alphas						
	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 7. Long-short breadth change portfolio alphas among subsamples

This table shows the one, three, and 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.

Panel A: One-factor alphas						
	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
1996-2001	-2.44**	-2.46**	-1.29*	-1.24**	-1.95**	0.09
	(0.30)	(0.30)	(0.57)	(0.27)	(0.25)	(0.47)
2002-2007	-1.58**	-1.55**	0.30	0.39*	-0.88**	1.13**
	(0.29)	(0.29)	(0.21)	(0.17)	(0.19)	(0.25)
Smallest size quintile	-1.73**	-1.75**	0.09	-0.60	-0.99**	0.31
	(0.32)	(0.33)	(0.51)	(0.34)	(0.32)	(0.41)
Largest size quintile	-2.21**	-2.20**	-0.11	0.22	-1.42**	1.51*
	(0.44)	(0.44)	(0.55)	(0.39)	(0.35)	(0.62)
No issuances or repurchases in last year	-1.95**	-1.93**	-0.35	-0.44*	-1.27**	0.69*
	(0.24)	(0.24)	(0.30)	(0.20)	(0.20)	(0.31)

Panel B: Three-factor alphas						
	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
1996-2001	-2.26**	-2.28**	-1.18*	-1.20**	-1.97**	0.29
	(0.30)	(0.31)	(0.59)	(0.28)	(0.27)	(0.48)
2002-2007	-1.57**	-1.54**	0.31	0.38*	-0.81**	1.07**
	(0.30)	(0.30)	(0.22)	(0.18)	(0.20)	(0.26)
Smallest size quintile	-1.66**	-1.69**	0.31	-0.44	-0.81*	0.33
	(0.33)	(0.34)	(0.51)	(0.33)	(0.31)	(0.41)
Largest size quintile	-2.07**	-2.06**	-0.20	0.28	-1.43**	1.68**
	(0.44)	(0.44)	(0.56)	(0.40)	(0.35)	(0.60)
No issuances or	-1.88**	-1.91**	-0.40	-0.43*	-1.27**	0.77*
repurchases in last year	(0.24)	(0.24)	(0.30)	(0.21)	(0.20)	(0.31)

Panel C: Four-factor alphas						
	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	-1.86**	-1.89**	-0.45	-0.44*	-1.26**	0.71*
repurchases in last year	(0.24)	(0.24)	(0.29)	(0.20)	(0.20)	(0.29)

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

Table 8. 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 2. "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. "Earnings announced" is a dummy variable for the company announcing earnings in month t. 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	0.202	0.238	0.095
	(0.088)	(0.098)	(0.096)	(0.092)	(0.141)	(0.263)	(0.115)
ΔEqual-weighted retail breadth$_{i,t}$			-39.540**	-37.554**	-28.319*	-35.886**	
			(4.539)	(4.685)	(12.866)	(5.962)	
Top 10% of Δwealth-weighted inst. breadth$_{i,t}$				0.606*	-0.362	0.003	
				(0.267)	(0.989)	(0.434)	
log(Total market cap$_{i,t}$)	-0.396	-0.266	-0.283	-0.300	0.349	-0.348	-0.350
	(0.203)	(0.210)	(0.208)	(0.205)	(0.423)	(0.257)	(0.209)
Book-to-market$_{i,t}$	1.343*	1.566**	1.319*	1.382*	2.189	-0.508	1.756**
	(0.575)	(0.555)	(0.548)	(0.548)	(1.122)	(0.999)	(0.536)
Return$_{i,t-11\rightarrow t-1}$ ÷ 100	0.763	1.051*	1.291*	1.267*	1.642	2.680*	1.021*
	(0.523)	(0.529)	(0.523)	(0.523)	(0.918)	(1.064)	(0.491)
Return$_{i,t}$ ÷ 100		-1.731	-5.855**	-6.158**	0.901	-4.849*	-5.694**
		(1.530)	(1.570)	(1.581)	(2.850)	(2.169)	(1.582)
Prior quarter turnover$_{i,t}$		-0.622**	-0.560*	-0.547*	-0.718	-0.329	-0.294
		(0.232)	(0.234)	(0.239)	(0.374)	(0.334)	(0.238)
Liquidity ratio$_{i,t}$		-1.934**	-1.898**	-1.910**	-3.317**	-2.921	-1.510*
		(0.635)	(0.631)	(0.673)	(1.015)	(1.701)	(0.748)

High relative volume$_{i,t}$		-0.643**	-0.529*	-0.518*	0.953	-0.131	-0.492*
		(0.246)	(0.246)	(0.248)	(1.780)	(0.305)	(0.240)
Low relative volume$_{i,t}$		0.231	0.178	0.189	-0.746	0.351	0.244
		(0.227)	(0.229)	(0.233)	(0.440)	(0.304)	(0.234)
Earnings announced$_{i,t}$					-0.409		
					(0.408)		
Earnings announced$_{i,t}$ × ΔEW retail breadth$_{i,t}$					-3.644		
					(15.576)		
Earnings announced$_{i,t}$ × Top 10% of ΔWW inst. breadth$_{i,t}$					0.913		
					(0.971)		
$\lambda_{i,t}$						-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*	-1.435	8.635*	8.000*
	(3.227)	(3.262)	(3.260)	(3.218)	(6.090)	(3.828)	(3.295)
# months	137	137	137	137	34	137	137
Average R^2	0.104	0.211	0.233	0.247	0.270	0.363	0.281

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

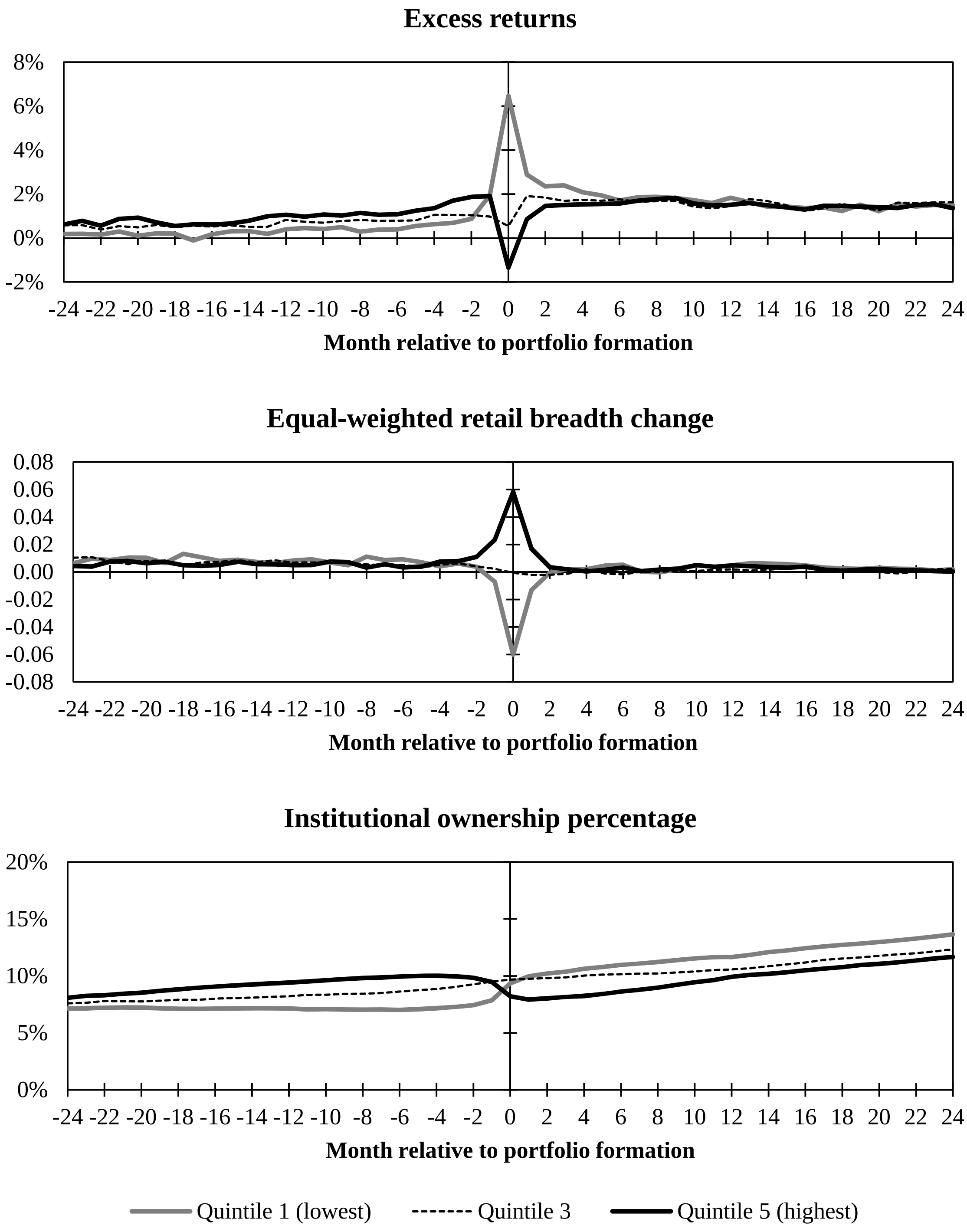

Figure 1. Returns, equal-weighted retail breadth change, and institutional ownership in 48-month window around portfolio formation date. The series shown represent statistics on portfolios formed on equal-weighted retail breadth change, as described in Tables 5 and 6.

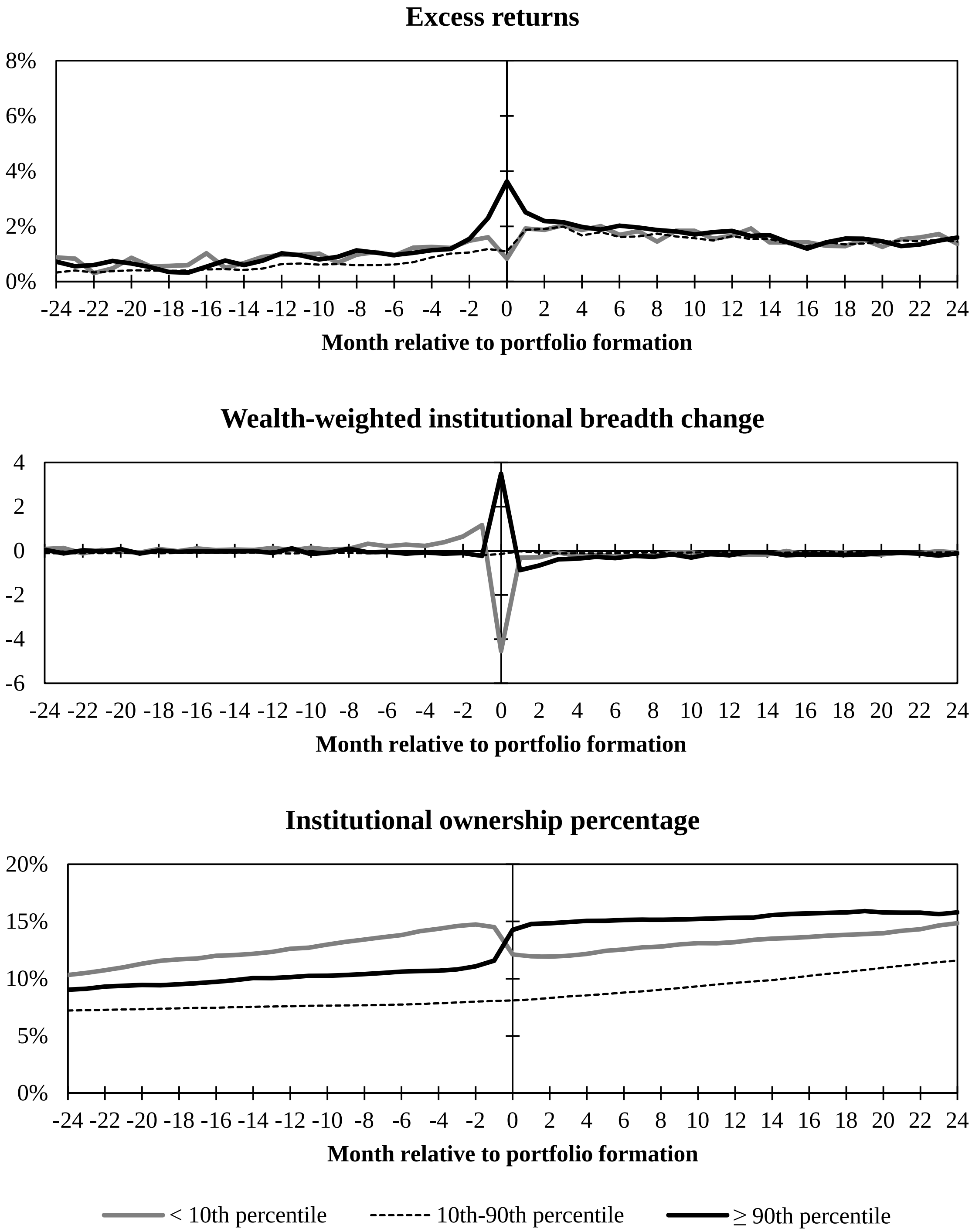

Figure 2. Returns, wealth-weighted institutional breadth change, and institutional ownership in 48-month window around portfolio formation date. The series shown represent portfolios formed on wealth-weighted institutional breadth change, as described in Tables 5 and 6.