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ABSTRACT

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

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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 and the time-series of aggregate stock market returns.

Chen, Hong, and Stein (2002) (hereafter CHS) argue that in a market where investors face short-sales constraints, few investors holding a stock long signals that there are many investors with bad fundamental news about the stock who would like to short it but cannot. These sidelined investors' negative information is not incorporated into the stock's price. Hence, low ownership breadth should lead to low future returns.[1] Their theory also implies that if many stocks' ownership breadth is lower than normal, then a lot of negative information in aggregate is missing from prices, so future aggregate market returns should be low *ceteris paribus*.

An alternative view of ownership breadth is that it is positively correlated with noise trader sentiment. Baruch (1960) describes the scene before the 1929 stock market crash: "Taxi drivers told you what to buy… An old beggar who regularly patrolled the street in front of my office now gave me tips and, I suppose, spent the money I and others gave him in the market. My cook had a brokerage account and followed the ticker closely. Her paper profits were quickly blown away in the gale of 1929." Joseph Kennedy Sr. is said to have gotten out of the stock market shortly before the crash because a shoeshine boy gave him stock tips. According to this story, when unsophisticated investors are buying en masse, causing ownership breadth to be high, future returns are low—the opposite of the relationship predicted by CHS.

Empirically testing ownership breadth's ability to predict future returns is challenging because comprehensive ownership data are generally not available at high frequency. Data constraints may explain why the evidence on the relationship between breadth and future returns has been mixed to date. CHS observe stock holdings only among mutual funds, not the entire

[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.

universe of investors, so their measure of ownership breadth is potentially biased.[2] 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. They find that cross-sectionally, stocks that are held by fewer mutual funds this period than last period 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.[3]

We use a new holdings dataset from the Shanghai Stock Exchange (SSE) that allows us to reassess the information content of ownership breadth and in addition differentiate between breadth among institutions versus breadth among retail investors. The investors in the data are a random, survivorship-bias-free sample of *all* investors in the SSE. At the end of each trading day from January 1996 to May 2007, the source data record each investor's complete SSE A-share[4] holdings. We obtain aggregated monthly ownership breadth change measures for each stock from these investor-level data. Short-sales are strictly prohibited in China, and during the period we study, there was no active derivatives market.

Our cross-sectional findings on the full investor sample contrast sharply with CHS. We find that high breadth change stocks subsequently *underperform* low breadth change stocks when we define ownership breadth as CHS do, giving equal weight to every investor. The annualized difference in the four-factor alpha between the highest and lowest quintiles of equal-weighted total breadth change is –23 percent, with a *t*-statistic of 9.7. Equal-weighted total breadth increases appear to primarily reflect greater popularity among noise traders, which causes overvaluation, rather than less negative fundamental information being missing from prices due to short-sales constraints. Two additional results are consistent with this interpretation.

First, based on the intuition that small investors are more likely to be noise traders, we redefine breadth change so that investors are weighted by their stock market wealth instead of being weighted equally. De-emphasizing the small retail investors who dominate the equal-

[2] CHS predict that ownership breadth *among all short-sales constrained investors only* is the relevant return predictor, so the mutual fund breadth measure is biased with respect to their theoretically relevant measure as well as with respect to breadth among all investors.

[3] 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.

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

weighted breadth measure, the annualized four-factor alpha difference between the highest and lowest breadth change portfolios attenuates to –5 percent (still statistically significant).

Second, we calculate breadth changes only among institutions, which seem less likely to be noise traders than individuals. To mitigate the influence of the many non-financial institutions that hold extremely small portfolios, we focus on wealth-weighted institutional breadth change. Portfolios formed on this measure 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 percent, with a *t*-statistic of 2.6. This suggests that in the cross-section, breadth among sophisticated institutional investors that cannot short primarily reflects how much of their negative information is not in the stock price, consistent with the CHS theory.[5] CHS do not model noise traders who observe no valid signals about fundamental values, so their theory ceases to apply once breadth is measured over a broader population that includes a large number of noise traders.

The negative relationship between equal-weighted total breadth changes and future returns comes entirely from retail investor breadth changes. The predictive ability of equal-weighted retail breadth changes is remarkably robust. It is present in both halves of the sample period, is somewhat stronger in the largest market cap quintile than the smallest market cap quintile, and is unaffected by excluding stocks less than one year removed from a share issuance or repurchase event (and thus does not appear to be related to the post-issuance and repurchase abnormal returns that have been documented in the U.S. market). Equal-weighted retail breadth change continues to predict returns up to five months after portfolio formation. Its predictive power survives controls for size, book-to-market, momentum, short-term return reversals, turnover, liquidity, change in the fraction of shares owned by institutions, and the shadow cost of incomplete information as formulated by Merton (1987) and empirically implemented by Bodnaruk and Ostberg (2009).

The predictive power of wealth-weighted institutional breadth changes is less robust than that of equal-weighted retail breadth changes. It is significant only in the second half of the sample, and only among large stocks. It predicts returns for only one month after portfolio

[5] Breadth among investors who are able to short is completely uninformative about how much negative information is missing from prices due to short-sales constraints.

formation. And although the highest wealth-weighted institutional breadth change decile outperforms in the future, the lowest decile does not underperform.

Institutions profit by trading against equal-weighted retail breadth changes. Institutional trades against retail investors are profitable in general (before transactions costs); if a stock's month-over-month change in the log fraction of shares owned by institutions is one standard deviation higher, its abnormal return in the subsequent month is 3.5 percent higher on an annualized basis. About 40 percent of that profitability is attributable to trading against equal-weighted retail breadth changes. Once we control for equal-weighted retail breadth change, a one standard deviation increase in log institutional ownership percentage change only predicts a (still statistically significant) 2.1 percent higher annualized abnormal return during the following month. When we additionally control for wealth-weighted institutional breadth change, the significance of institutional ownership percentage change disappears, but wealth-weighted institutional breadth change remains a significant positive predictor of future returns. Thus, changes in institutional ownership percentage appear to predict high future returns only to the extent that they are correlated negatively with retail breadth changes and positively with institutional breadth changes.

Whereas the prior empirical literature has restricted its attention to cross-sectional tests, the high frequency of our data allows us to conduct time-series tests as well. We use the market-capitalization-weighted average of breadth changes across stocks within a single month as our predictive variable. Our findings are again contrary to the story that total breadth is a proxy for how much negative information is missing from prices due to short-sales constraints: high average total breadth change this month predicts *low* aggregate Chinese stock market returns next month. This negative predictive power is statistically significant for the average of wealth-weighted total breadth changes, but not for the average of equal-weighted total breadth changes, which is somewhat surprising in light of our cross-sectional results. As in the cross-section, the time-series negative relationship between total breadth change and future returns is driven by retail investors.

There is no robust evidence that average institutional breadth change predicts aggregate market returns. This is again surprising given our cross-sectional evidence. One might have expected average wealth-weighted institutional breadth increases to be a bullish signal. The absence of such a relationship could arise from retail sentiment affecting inflows to and redemptions from aggregate assets under management that must be invested in equities. Net inflows may increase the *number* of stock positions institutions hold due to concerns about the price impact of buying additional shares of stocks in which they already own a large fraction of the float. Thus, changes over time in average institutional breadth—which is roughly equivalent to changes in the number of positions per institution divided by the total number of stocks[6]—may contain a significant retail sentiment component. However, if institutions can pick stocks that are relatively better at a given point in time, institutional breadth would be positively correlated with future returns in the cross-section, as we observe in the data.

Our last piece of analysis examines whether ownership breadth changes predict the skewness of individual stock returns in the cross-section and the skewness of aggregate market returns in the time series. Hong and Stein (2003) suggest that crashes should be preceded by narrowing ownership breadth due to a mechanism similar to that in CHS: narrowing ownership breadth indicates that bad news is being excluded from market prices due to short-sales constraints. A small price drop that does not cause sidelined investors to begin buying can reveal that the excluded news is extremely bad, resulting in a larger price drop. In contrast, a small price increase does not trigger a larger price increase because there is no good news that had previously been withheld due to portfolio constraints.

We find limited support for the Hong and Stein (2003) model. In the cross-section, breadth changes do not predict future individual stock skewness. In the time series, the average total wealth-weighted breadth change positively predicts the skewness of daily market returns during the following month in a univariate regression. But the statistical significance of this result is not robust to additionally controlling for the lagged market return and the lagged change in the fraction of the market owned by institutions.

Our paper contributes to the literature that attempts to empirically detect the price impact of short-sales constraints.[7] In addition, our paper is related to others that seek to identify the

[6] Average institutional breadth change would exactly equal this quantity if each stock received equal weight in the average.

[7] 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)).

impact individual investors have on prices and the portfolio performance of institutional and individual investors.[8]

The remainder of the paper is organized as follows. Section I describes our data. Section II describes the variables we use in the analysis. Section III presents results on predicting the cross-section of stock returns and return skewness, and Section IV presents results on predicting the time-series of aggregate market returns and return skewness. Section V concludes.

I. Data Description

Our ownership breadth data come from the Shanghai Stock Exchange. At the end of 2007, the 860 stocks traded on the Shanghai Stock Exchange had a total market capitalization of $3.7 trillion, making it the world's sixth-largest stock exchange (behind NYSE, Tokyo, Euronext, Nasdaq, and London). China's other stock exchange, the Shenzhen Stock Exchange, had a $785 billion market capitalization at year-end 2007.

To trade on the Shanghai Stock Exchange, both retail and institutional investors are required to open an account with the Exchange. Each account uniquely and permanently identifies an investor, even if the account later becomes empty. Investors cannot have multiple accounts. The individual account data assembled by the Exchange for this paper consists of a representative random sample of all accounts that existed at the end of May 2007.[9] Since this sample contains both currently active and inactive accounts, there is no survivorship bias. Individual tradable[10] A-share holdings in the sample are aggregated at the Exchange into stock-

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

[9] The Exchange extracted all account information from a randomly selected sample of all retail investor accounts. The Exchange followed a similar procedure to obtain a random sample of institutional accounts. However, 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 used to generate aggregate statistics. The market-wide statistics computed from these account data are reweighted to adjust for the over-sampling of institutional investors. Further details of the sampling process can be obtained from the authors.

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

level measures. The aggregation is carried out under arrangements that maintain strict confidentiality requirements to ensure that no individual account data are disclosed.

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

II. Variable Definitions

A. Cross-sectional analysis variables

Following CHS, we define the equal-weighted total ownership breadth change of stock i in month t in the following way. We first restrict the sample to investors who have a long position in at least one SSE stock at the end of both $t-1$ and t. This restriction ensures that the breadth change measure captures only the trading activity of existing market participants, rather than changes in the investor universe due to new market participants entering and institutions dissolving. 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.

If equal-weighted breadth change is negatively correlated with future returns because it reflects noise trader sentiment, then de-emphasizing small investors—who are likely to be less sophisticated[11]—in the breadth change measure should attenuate this negative relationship. We thus additionally use an alternative measure of ownership breadth not found in CHS that weights investors by the value of their SSE portfolio. 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

[11] 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 noise traders' wealth share.

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

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 equals IN minus OUT. Wealth-weighted IN and OUT are defined analogously. For example, wealth-weighted IN is the month t opening SSE stock portfolio value of subsample investors who moved from a zero position to a positive position in stock i between $t-1$ and t divided by the month t opening SSE stock portfolio value of all subsample investors.

Our main cross-sectional analysis involves evaluating the return performance of portfolios formed on breadth changes. We estimate four-factor alphas, where the factor portfolio returns capture CAPM beta, size, value, and momentum effects. The market portfolio return is the composite Shanghai and Shenzhen market return, weighted by tradable market capitalization. The riskfree return is the demand deposit rate. We construct size and value factor returns (SMB 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.[12] 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

[12] 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.

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 *t* is used as the predictor from July of year *t* through June of year *t* + 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 past month, Amivest liquidity ratio during the prior month, and shadow cost of incomplete information. We operationalize the Amivest liquidity ratio as the sum of the stock's yuan trading volume over one month divided by the sum of the stock's absolute daily returns over that month. Higher values of the liquidity ratio correspond to lower price impacts of trading, and hence higher liquidity. The shadow cost of incomplete information, λ, captures abnormal returns due to Merton's (1987) "investor recognition hypothesis" that investors neglect to hold stocks they are unaware of, causing the investors who do hold these neglected stocks to sacrifice diversification and hence demand a higher expected return. Investor recognition is closely related to ownership breadth changes and so should be controlled for. We adopt the operationalization of λ used by Bodnaruk and Ostberg (2009):

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

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

We also test the ability of breadth changes to predict future return skewness. Our measure of return skewness is the skewness of daily returns over one month.

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

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

B. Time-series analysis variables

The predictor of aggregate market returns we test is the average breadth change of all SSE stocks during a month weighted by each stock's tradable market capitalization at the end of the prior month. Table 2 reports summary statistics for average breadth change. The mean average wealth-weighted breadth change is negative in all investor populations, as is the mean average equal-weighted institutional breadth change. Average equal-weighted total and retail breadth changes have slightly positive means. The average institutional breadth change measures are substantially more volatile than the average retail breadth change measures. The standard deviation of average equal-weighted institutional breadth change is almost twice that of average equal-weighted retail breadth change, and the standard deviation of average wealth-weighted institutional breadth change is more than ten times that of average wealth-weighted retail breadth change. The average retail breadth change measures exhibit much more autocorrelation than the average institutional breadth change measures. Average equal-weighted retail breadth change, for example, has an autocorrelation of 0.322, whereas average equal-weighted institutional breadth change's autocorrelation is only 0.076.

The time series of aggregate equal- and wealth-weighted breadth change measures are plotted in Figures 1 and 2. The retail measures are more volatile at the beginning of the sample and gradually become more stable before experiencing another increase in volatility towards the end of the sample. In contrast, the volatility of average institutional breadth change remains relatively high throughout our sample period.

The dependent variables we are interested in predicting with average breadth change are the Shanghai/Shenzhen market return in the next month and the skewness of daily Shanghai/Shenzhen market returns during the next month. The average monthly market return during our sample period is 2.1%, with a standard deviation of 9.0% and an autocorrelation of 0.17. The daily market return skewness during a month has a time-series average of –0.09, with a standard deviation of 0.88 and an autocorrelation of 0.25. (These market return statistics are not displayed in a table.)

III. Cross-Sectional Results

A. Main portfolio-based return forecasting tests

We first test the ability of breadth changes to predict the cross-section of returns by using breadth changes to form portfolios. Following CHS, at the end of each month t, we sort stocks into tradable market capitalization quintiles, and then calculate breakpoints within each size quintile based on breadth change during t. We weight stocks by tradable market capitalization within each size × breadth change sub-portfolio. The volatility of breadth change increases with firm size, which is why we and CHS calculate different breadth change breakpoints for each size quintile; otherwise, the extreme quintiles of breadth change would be dominated by large firms. To form the "Quantile n" portfolio, we equally weight across size quintiles the five nth quantile breadth change sub-portfolios, and hold the stocks for one month before re-forming the portfolios at the end of month $t + 1$.

Table 3 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. This return differential barely falls to 202 basis points per month (24.2% per year) when we adjust for CAPM beta risk, and to 194 basis points per month (23.3% per year) with a t-statistic of 9.7

when we additionally adjust for size, value, and momentum effects.[13] Abnormal returns come not only from underperformance in the highest total breadth change portfolio (which cannot be shorted), but also from outperformance in the lowest total breadth change portfolio, which has a significant positive four-factor alpha of 112 basis points per month (13.4% per year). These results are contrary to the CHS model, which predicts that future returns are *increasing* in ownership breadth, since high breadth means fewer investors with bad news are sitting on the sidelines. Instead, the results appear consistent with stocks becoming overvalued when they gain popularity and undervalued when they lose popularity.[14]

The right half of Table 3, Panel A provides evidence supportive of the story that total equal-weighted breadth changes primarily reflect noise trader sentiment. If wealthy investors are less likely to be noise traders, then weighting breadth changes by investor wealth should decrease the spread between high and low breadth change stocks. Indeed, the raw return difference between the lowest and highest breadth change quintiles falls to 36 basis points per month (4.3% per year) when we use wealth-weighted total breadth change to form portfolios, although this difference remains significant at the 5% level. Adjusting the difference by the one-factor or four-factor model yields slightly larger and still-significant alphas: 45 basis points and 42 basis points per month (5.4% and 5.0% per year), respectively.

Further evidence in favor of the noise trader story comes from Panels B and C of Table 3, 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.

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[13] 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.

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

It seems plausible that institutions are less likely to be noise traders than individuals, which suggests that institutional breadth change should not be a contrarian indicator. We do in fact see in the left half of Panel C that stocks experiencing large equal-weighted institutional breadth increases do not significantly underperform stocks experiencing large equal-weighted institutional breadth decreases. The 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 nearly identical to those of portfolios formed on equal-weighted total breadth changes. As we previously noted in Section II.A, 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 even among individuals, forming portfolios based on wealth-weighted breadth change decreases the spread between the high and low breadth change portfolio returns. The four-factor alpha of the difference between the lowest and highest wealth-weighted retail breadth change portfolios is 142 basis points per month (17.0% per year), which is smaller than the 194 basis point per month difference between the lowest and highest equal-weighted retail breadth change portfolios (albeit not significantly so).

Among institutions, portfolios formed on wealth-weighted breadth changes reproduce the CHS empirical result: the high wealth-weighted institutional breadth change portfolio significantly outperforms the low wealth-weighted institutional breadth change portfolio by 58, 60, and 67 basis points per month (7.0%, 7.2%, and 8.0% per year) on a raw, one-factor-adjusted, and four-factor-adjusted basis, respectively. Unlike CHS's empirical results, however, the abnormal returns are present only in the high breadth change portfolio and are absent from the low breadth change portfolio. We speculate that the absence of abnormal negative returns in the low breadth change portfolio is due to institutional breadth decreases reflecting not only negative information but also the need to service customer redemptions.

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

B. Persistence of portfolio-based return results

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

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

Table 4 shows the average return spreads adjusted for size, value, and momentum effects for $n = 2, 3, \ldots, 12$. Equal-weighted retail breadth change significantly predicts returns in every month up to five months into the future. At month $t + 5$, the difference between the highest and lowest breadth change portfolio alphas is still –42 basis points (–5.0% annualized). Even though the alpha differences are no longer significant from months $t + 6$ to $t + 12$, they are all negative with the exception of month $t + 9$. Wealth-weighted retail breadth change shows a similar amount of predictive persistence; the alpha difference between the highest and lowest wealth-weighted retail breadth change quintiles stops being significant after month $t + 5$, with the exception of a significant negative spread at $t + 10$. Comparing the equal-weighted to the wealth-weighted retail alpha differences at each horizon, we see that from t to $t + 5$, equal-weighted retail breadth change always predicts a larger spread than wealth-weighted retail breadth change, consistent with our $t + 1$ results in Table 3.

In contrast, institutional breadth change does not significantly predict returns beyond one month, whether breadth changes are equal- or wealth-weighted. None of the alpha differences in

Table 4 under the institutional columns is significant. However, it is notable that for wealth-weighted institutional breadth change, the alpha difference point estimates are positive in nine out of the eleven time horizons.

As in Table 3, the predictive power of total breadth change beyond the first month is driven by retail investors. The alpha spreads between the highest and lowest equal-weighted total breadth change quintiles are almost the same as those between the highest and lowest equal-weighted retail breadth change quintiles. For portfolios formed on wealth-weighted total breadth change, where institutions have more influence, the alpha spread disappears beyond the first month.

C. Robustness of portfolio-based return results

In this subsection, we replicate our main portfolio-based analysis 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. The fifth subsample excludes companies if they 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 5 shows, for each subsample, the four-factor alpha spread between the highest breadth change and lowest breadth change quantiles in the first month after stocks are sorted by breadth change. The retail breadth change results, whether equal-weighted or wealth-weighted, are robustly present in all subsamples. Unlike many return anomalies documented in the literature, the predictive power of retail breadth change is (insignificantly) stronger among large stocks than small stocks. Excluding recent issuers and repurchasers has no effect on the results. Interestingly, the magnitudes of the retail alpha spreads in the first half of the sample are significantly larger than those in the second half. This could be consistent with increasing sophistication of retail investors over time or increasing aggressiveness of institutional investors over time in betting against retail breadth changes, thus attenuating future abnormal returns.

In contrast, the alpha spreads for portfolios formed on institutional breadth change are not significant in some subsamples. Equal-weighted institutional breadth change portfolios continue not to significantly predict returns in all subsamples. Wealth-weighted institutional breadth change generates a significant alpha spread only in the second half of the sample; in the first half, the spread is 45 basis points per month (5.4% per year) but insignificant, whereas in the second half, it is 106 basis points per month (12.7% per year) and highly significant. Wealth-weighted institutional breadth change also significantly predicts returns only among large stocks (alpha spread of 161 basis points per month, or 19.2% per year), not small stocks (insignificant alpha spread of 33 basis points per month, or 4.0% per year). The wealth-weighted institutional breadth change results are not affected, however, by excluding recent issuers and repurchasers. These differences in alphas across subsamples could be due to an increase in sophistication among domestic financial institutions over time, the entry of sophisticated foreign institutions into the SSE in 2003, and the fact that financial institutions tend to focus their attention on large stocks.

D. Do institutions profit at the expense of retail investors?

Our results thus far show that when a stock becomes held by more retail investors, its future returns are low, whereas when it becomes held by more institutions, its future returns are high. A natural question then arises: do institutions 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 Sections III.A through III.C.

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 6 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 percent of shares owned by institutions, 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 6 additionally controls for the current month's stock return, the sum of turnover during the current month and prior two months, and the Amivest liquidity ratio during the current month. These extra controls cause the point estimate on log institutional ownership percentage change to rise, so that a one standard deviation higher log institutional ownership percentage change predicts an increase in the stock's return next month of 0.29%, or 3.5% on an annualized basis.

How much of the profitability of institutional trading is accounted for by institutions trading against equal-weighted retail breadth changes? The third column of Table 6 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 remains significantly positive, albeit with a point estimate that is 58% that in the second column. It thus appears that trading against equal-weighted retail breadth changes accounts for about 40% of the profitability of institutional trades against retail investors, but institutions have some other source of useful information in addition to what is captured by retail breadth changes.

The fourth column of Table 6 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 3 (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 loses its significance, but being in the top 10 percentiles of wealth-weighted institutional breadth change remains a significantly positive predictor of future returns. In other words, changes in institutional ownership unrelated to equal-weighted retail breadth changes are useful for predicting future returns only to the extent that they are correlated with an increase in wealth-weighted institutional ownership breadth (in the CHS theoretical framework, a decrease in the negative information excluded from the stock price).

E. 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 causes 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.[15]

The penultimate column of Table 6 shows coefficients from a Fama-MacBeth regression where the dependent variable is next month's return and the explanatory variables are λ and the full set of other controls—change in log institutional ownership percentage, equal-weighted retail breadth change, a dummy for being in the top 10 percentiles of wealth-weighted institutional breadth change within the stock's size quintile, log total market capitalization, book-to-market, prior year return excluding the current month, current month return, prior quarter turnover, and liquidity ratio. 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 is negative and 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 6, where we did not control for λ.[16]

F. Ownership initiations versus discontinuations

In this subsection, we explore whether ownership initiations have different information content than ownership discontinuations. Recall that by construction, breadth change equals IN

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

[16] Note, however, that in addition to the difference in explanatory variables, the sample in the fourth column of Table 6 is not the same as the sample in the last two columns. 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.

(the fraction of investors who initiate ownership) minus OUT (the fraction of investors who discontinue ownership). The last column of Table 6 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 other control variables we have used up to now. The estimates show that the only component of retail breadth change that predicts returns is IN; retail OUT has no significant predictive power. We speculate that this asymmetry is due to new purchases of a stock being driven by changes in perceived valuation, whereas complete close-outs of positions are often driven by liquidity needs and the disposition effect (Shefrin and Statman, 1985; Odean, 1998) and thus carry less information about general retail sentiment. Neither institutional IN or OUT are significant return predictors in this comprehensive specification.

G. Predicting return skewness

In Table 7, we show the results of Fama-MacBeth regressions that test breadth change's ability to predict the skewness of daily individual stock returns in the following month. The breadth measure or measures used as predictors differ across the four specifications in the table: (1) equal-weighted total breadth change, (2) wealth-weighted total breadth change, (3) equal-weighted retail breadth change and wealth-weighted institutional breadth change, and (4) equal-weighted retail breadth change and a dummy for a stock being in the month's top 10 percentiles of wealth-weighted institutional breadth change within its size quintile. All specifications also control for the other non-breadth-change-related explanatory variables we used previously.

We find no evidence that breadth changes predict future return skewness. The point estimates of the breadth change variable coefficients are generally negative—the opposite of what the Hong and Stein (2003) intuition would suggest—and always insignificant.

H. Cross-sectional correlates of breadth change

We analyze the correlates of breadth change by running Fama-MacBeth regressions of breadth change on contemporaneous and lagged variables. The $t + 1$ breadth change measures we analyze are the following: total, retail, and institutional equal-weighted breadth change; total, retail, and institutional wealth-weighted breadth change; and a dummy for a stock being in the month's top 10 percentiles of wealth-weighted institutional breadth change within its size quintile. The explanatory variables are log of total market capitalization at t, book-to-market at t, the stock's return from $t – 11$ to $t – 1$, the stock's t return, the stock's $t + 1$ return, the change in log institutional ownership percentage during t, the sum of monthly turnover from $t – 2$ to t, liquidity ratio at t, and number of years since the firm's IPO as of t.

Table 8 shows that equal-weighted retail breadth increases among growth stocks, stocks that have experienced recent institutional ownership percentage decreases, stocks that have had high recent turnover, and younger stocks. There is no significant tendency for retail ownership breadth to increase among liquid or small stocks. Consistent with previous empirical findings in other countries on retail investor reactions to returns (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)), retail investor breadth change is contrarian with respect to contemporaneous month returns but trend-chasing with respect to returns more distant in the past. This pattern of responses suggests that retail investors inhibit initial price reaction to news but may eventually cause overreaction. Wealth-weighted retail ownership breadth change behavior is similar with respect to returns and growth stocks, but there is no significant relationship with the other variables.

Wealth-weighted institutional breadth change, on the other hand, is positively correlated with returns at all horizons. Top-ten-percentile increases in institutional ownership breadth also tend to occur in large, more liquid stocks that have had high turnover and recent increases in institutional ownership percentage.

IV. Time-Series Results

A. Predicting market returns

To test the ability of breadth change to predict aggregate stock market returns, we run regressions of the aggregate Shanghai/Shenzhen market excess return on lagged average breadth change across SSE stocks weighted by tradable market capitalization. In a second specification, we also control for the previous period's market return and the change in the log percent of SSE tradable market capitalization owned by institutions. Panel A of Table 9 shows that average wealth-weighted total breadth change is a significant negative predictor of next month's market return under both regression specifications. The economic magnitude is large: a one standard deviation increase in average wealth-weighted total breadth change predicts a $23.616 \times 0.119 = 2.81\%$ lower market return next month in the multivariate regression. This is consistent with the cross-sectional evidence that higher total breadth change leads to lower subsequent returns. A high average ownership breadth increase may indicate that investors have become overly excited about stocks in general. Given that equal-weighted total breadth change has stronger predictive power than wealth-weighted total breadth change in the cross-section, it is somewhat surprising that the coefficient on average equal-weighted total breadth change is insignificant, although it too is negative.

We repeat the regressions using the average retail breadth change and institutional breadth change measures. The results are reported in Panels B and C of Table 9. The retail breadth change results are similar to the total breadth change results: higher average breadth change leads to lower subsequent returns, but this effect is significant only for average wealth-weighted retail breadth change. Average institutional breadth change always has a negative coefficient, but it is significant only in the univariate regression with the equal-weighted measure. The economic magnitude here is also large; a one standard deviation increase in average equal-weighted institutional breadth change predicts a $18.295 \times 0.082 = 1.50\%$ lower market return next month in the univariate regression. Again, it is somewhat surprising in light of the cross-sectional results that average wealth-weighted institutional breadth change does not positively predict future market returns.[17]

B. Predicting market return skewness

We test the ability of breadth change to forecast negative market return skewness by regressing daily market return skewness during the next month on the average change in breadth during the current month. The intuition of Hong and Stein (2003) suggests that we should expect a positive coefficient in our regressions.

Panel A of Table 10 shows that in a univariate regression, the coefficient on average wealth-weighted total breadth change is significantly positive, as predicted. However, this

[17] Because the breadth change measures are not highly persistent and are not scaled price variables, the finite-sample bias documented in Mankiw and Shapiro (1986), Stambaugh (1986), Nelson and Kim (1993), and Stambaugh (1999) is of lesser concern. We have re-run the univariate regressions correcting for this bias using the methodology of Amihud and Hurvich (2004) and found that the coefficients and standard errors are nearly unchanged.

relationship is not robust to including controls for the prior month's market return and change in log aggregate institutional ownership percentage. Average equal-weighted total breadth change is not a significant predictor in either specification. Panels B and C show that none of the retail and institutional breadth change measures predict future skewness. Interestingly, in all our specifications, the prior-month return is a significant negative predictor for future skewness. This negative relationship between current return and future skewness is also found in U.S. data (Chen, Hong, and Stein (2001)).

C. Correlates of average monthly breadth changes

To find the correlates of average monthly breadth changes, we regress the various average breadth change measures on their own lag, the contemporaneous and lagged market return, and the lagged change in log percent of SSE tradable A-share market capitalization owned by institutions. The results are contained in Table 11.

There are a few significant relationships. Average equal-weighted institutional breadth change is negatively correlated with the contemporaneous market return. Average wealth-weighted total, retail, and institutional breadth changes are all negatively correlated with the lagged market return. Average wealth-weighted retail breadth change is also significantly predicted by its own lag. The coefficients on market returns show that investor reactions to cross-sectional variation in returns are quite different from investor reactions to time-series variation in aggregate market returns.

V. Conclusion

We have tested the ability of ownership breadth changes to predict stock returns in both the cross-section and the time-series. When we restrict the sample over which we measure breadth to institutional investors, we find cross-sectional support for 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: a large increase in the number of institutions (on a wealth-weighted basis) that hold a stock in a given month predicts a high stock return the following month. When we measure breadth changes among retail investors, the sign of the breadth change effect flips: higher ownership breadth change predicts dramatically lower returns for the next five months. Thus, it appears that retail breadth changes primarily reflect sentiment. The profitability of institutional trades against individuals is almost entirely explained by their correlations with retail and institutional breadth changes. In the time series, we find that higher average ownership breadth change across stocks in a given month generally predicts lower aggregate market returns during the next month.

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

The cross-sectional means and standard deviations are calculated separately within each month. The table reports the time-series average of these means and standard deviations. Equal-weighted total breadth change is the change between month-ends $t-1$ and t in the number of investors holding stock i divided by the total number of investors. Wealth-weighted total breadth change is like equal-weighted total breadth change, but weights investors by the value of their SSE stock portfolio at the open of month t. Institutional and retail breadth changes are defined analogously on the retail or institutional subsample. Equal-weighted retail IN is the percent of retail investors who held no position in the stock at $t-1$ but held a positive position in it at t. Equal-weighted retail OUT is the percent of retail investors who held a positive position in the stock at $t-1$ but held no position in it at t. Wealth-weighted institutional IN and OUT are defined analogously over institutions, weighting them by their SSE stock portfolio value at the open of month t. Breadth changes, IN, and OUT are expressed as percentages, so that a 1 percent value is coded as 1, rather than 0.01. The variable $\lambda_{i,t}$ is the Merton shadow cost of incomplete information defined in equation (2), and 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.

	Mean	Standard deviation
Return$_{i,t+1}$	1.944	9.422
Daily stock return skewness$_{i,t+1}$	0.150	0.612
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

Table 2. Average breadth change time series summary statistics

This table shows summary statistics for the average breadth change across all SSE stocks during month t weighted by each stock's tradable market capitalization at the end of $t-1$. Depending on the column, each component stock's breadth change is either equal-weighted or wealth-weighted and defined over all, retail, or institutional investors.

	Average equal-weighted breadth change			Average wealth-weighted breadth change		
	Total	Retail	Institutional	Total	Retail	Institutional
Mean	0.009	0.009	-0.026	-0.074	-0.045	-0.296
Std. dev.	0.045	0.045	0.082	0.119	0.086	0.871
Autocorrelation	0.322	0.322	0.076	0.329	0.404	-0.116
N	137	137	137	137	137	137

Table 3. Monthly returns on breadth change portfolios

This table shows the raw return in excess of the riskfree rate, CAPM alpha, and four-factor alpha from portfolios that are formed based on the prior month's equal- or wealth-weighted breadth change among the total, retail, or institutional investor sample. At the end of each month *t*, we first sort stocks into tradable market capitalization quintiles, and then calculate month *t* breadth change breakpoints within each size quintile. We value-weight stocks within each market cap × breadth change sub-portfolio. For the total and retail investor samples, to form the "Quintile *n*" portfolio, we equally weight across the market cap quintiles the five *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	4-factor alpha	Raw return	CAPM alpha	4-factor alpha
Quintile 1	2.87**	1.01**	1.12**	2.18**	0.37	0.52**
(lowest breadth change)	(0.77)	(0.27)	(0.21)	(0.74)	(0.25)	(0.19)
Quintile 2	2.41**	0.49	0.58**	2.16**	0.28	0.35*
	(0.79)	(0.27)	(0.17)	(0.77)	(0.27)	(0.17)
Quintile 3	1.93*	0.13	0.28	1.91*	0.03	0.15
	(0.74)	(0.26)	(0.18)	(0.79)	(0.31)	(0.19)
Quintile 4	1.80*	-0.09	0.04	1.70*	-0.15	-0.03
	(0.78)	(0.27)	(0.19)	(0.77)	(0.28)	(0.19)
Quintile 5	0.84	-1.01**	-0.83**	1.82*	-0.08	0.10
(highest breadth change)	(0.76)	(0.28)	(0.20)	(0.77)	(0.23)	(0.17)
5 – 1	-2.04**	-2.02**	-1.94**	-0.36*	-0.45*	-0.42*
	(0.20)	(0.21)	(0.20)	(0.18)	(0.18)	(0.18)

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

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

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

Table 4. Persistence of long-short breadth change portfolio four-factor alphas

This table shows the four-factor alphas from zero-investment portfolios that are formed based on breadth change that is either equal- or wealth-weighted among all, retail, or institutional investors. To form the "Month $t + n$" 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 $t + n - 1$ 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 $t + n$ before stocks are re-sorted into (possibly) new portfolios. Standard errors are in parentheses.

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

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

Table 5. Long-short breadth change portfolio four-factor alphas among subsamples

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

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
1996-2001	-2.34**	-2.37**	-1.08	-1.17**	-2.02**	0.45
	(0.28)	(0.29)	(0.58)	(0.28)	(0.26)	(0.43)
2002-2007	-1.54**	-1.52**	0.31	0.38*	-0.80**	1.06**
	(0.30)	(0.30)	(0.22)	(0.18)	(0.20)	(0.26)
Smallest size quintile	-1.66**	-1.68**	0.32	-0.41	-0.78*	0.33
	(0.33)	(0.34)	(0.51)	(0.33)	(0.31)	(0.42)
Largest size quintile	-2.04**	-2.03**	-0.26	0.22	-1.45**	1.61**
	(0.44)	(0.43)	(0.54)	(0.38)	(0.35)	(0.58)
No issuances or	-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 6. Future returns: Fama-MacBeth regressions

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

Δlog(Institutional Ownership$_{i,t}$)	0.333**	0.365**	0.213**	0.125	0.230	0.093
	(0.088)	(0.082)	(0.080)	(0.081)	(0.318)	(0.267)
ΔEqual-weighted retail breadth$_{i,t}$			-40.881**	-39.003**	-32.654**	
			(4.587)	(4.716)	(5.267)	
Top 10% of Δwealth-weighted inst. breadth$_{i,t}$				0.609*	-0.014	
				(0.281)	(0.405)	
log(Total market cap$_{i,t}$)	-0.396	-0.265	-0.282	-0.296	-0.373	-0.422
	(0.203)	(0.208)	(0.206)	(0.203)	(0.227)	(0.241)
Book-to-market$_{i,t}$	1.343*	1.549**	1.286*	1.349*	0.847	0.627
	(0.575)	(0.559)	(0.553)	(0.552)	(0.648)	(0.773)
Return$_{i,t-11\rightarrow t-1}$ ÷ 100	0.763	1.098*	1.320*	1.293*	1.353	0.868
	(0.523)	(0.524)	(0.520)	(0.521)	(0.736)	(0.966)
Return$_{i,t}$ ÷ 100		-2.305	-6.071**	-6.424**	-5.855**	-4.192*
		(1.484)	(1.523)	(1.541)	(1.920)	(2.018)
Prior quarter turnover$_{i,t}$		-0.573*	-0.542*	-0.516*	-0.594	-0.629
		(0.231)	(0.232)	(0.238)	(0.437)	(1.009)
Liquidity ratio$_{i,t}$		-2.019**	-1.899**	-1.977**	-0.563	0.630
		(0.621)	(0.610)	(0.640)	(1.960)	(4.362)

$\lambda_{i,t}$					-1.278	-3.272
					(20.164)	(21.937)
Equal-weighted retail $IN_{i,t}$						-54.406**
						(8.540)
Equal-weighted retail $OUT_{i,t}$						14.528
						(8.213)
Wealth-weighted inst. $IN_{i,t}$						11.887
						(8.240)
Wealth-weighted inst. $OUT_{i,t}$						-1.553
						(4.271)
Constant	7.254*	6.800*	6.988*	7.121*	8.069*	9.712**
	(3.227)	(3.240)	(3.237)	(3.190)	(3.519)	(3.703)
# months	137	137	137	137	137	137
Average R^2	0.104	0.185	0.207	0.222	0.334	0.377

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

Table 7. Future return skewness: Fama-MacBeth regressions

This table shows coefficients from a monthly Fama-MacBeth regression where the dependent variable is the stock's daily return skewness during month $t + 1$. 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. The explanatory variables are as defined in Tables 1 and 6. Average R^2 is the average of the cross-sectional regressions' R^2 values.

ΔEqual-weighted total breadth$_{i,t}$	-0.536			
	(0.412)			
ΔWealth-weighted total breadth$_{i,t}$		-0.297		
		(0.230)		
ΔEqual-weighted retail breadth$_{i,t}$			-0.511	-0.741
			(0.437)	(0.402)
ΔWealth-weighted inst. breadth$_{i,t}$			0.022	
			(0.179)	
Top 10% of Δwealth- weighted inst. breadth$_{i,t}$				-0.025
				(0.028)
$\lambda_{i,t}$	4.376**	4.758**	4.124**	2.462
	(1.220)	(1.450)	(1.328)	(1.629)
Δlog(Institutional Ownership$_{i,t}$)	0.013	0.160	0.024	0.004
	(0.101)	(0.110)	(0.031)	(0.020)
log(Total market cap$_{i,t}$)	0.032	0.073**	0.031	0.053**
	(0.025)	(0.019)	(0.018)	(0.014)
Book-to-market$_{i,t}$	-0.014	-0.062	-0.033	-0.038
	(0.056)	(0.057)	(0.055)	(0.054)
Return$_{i,t-11\rightarrow t-1}$ ÷ 100	-0.131	0.109	-0.111	0.015
	(0.161)	(0.099)	(0.134)	(0.056)
Return$_{i,t}$ ÷ 100	0.004	0.000	-0.001	-0.004
	(0.011)	(0.002)	(0.007)	(0.002)
Prior quarter turnover$_{i,t}$	-0.091*	-0.032	-0.019	-0.021
	(0.041)	(0.036)	(0.038)	(0.035)
Liquidity ratio$_{i,t}$	-0.070	-0.054	-0.246	-0.166
	(0.120)	(0.131)	(0.181)	(0.181)
Constant	-0.225	-0.833**	-0.248	-0.592**
	(0.433)	(0.244)	(0.302)	(0.205)
# months	137	137	137	137
Average R^2	0.249	0.249	0.267	0.267

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

Table 8. Cross-sectional correlates of breadth change

This table shows coefficients from a monthly Fama-MacBeth regression where the dependent variable is equal- or wealth-weighted breadth changes in month $t + 1$ among all, retail, or institutional investors. In the last column, the dependent variable is a dummy for a stock being in the top 10 percentiles of month $t + 1$'s wealth-weighted institutional breadth change distribution within its tradable market capitalization quintile. 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. The explanatory variables are as defined in Tables 1 and 6. Average R^2 is the average of the cross-sectional regressions' R^2 values.

	Equal-weighted breadth change			Wealth-weighted breadth change			
	Total	Retail	Inst.	Total	Retail	Inst.	Top 10% of inst.
log(Total market cap$_{i,t}$)	-0.002	-0.002	-0.003	-0.009*	-0.005	-0.006	0.024**
	(0.001)	(0.001)	(0.003)	(0.004)	(0.003)	(0.034)	(0.004)
Book-to-market$_{i,t}$	-0.014**	-0.014**	-0.005	-0.019	-0.017**	0.054	0.015
	(0.003)	(0.003)	(0.008)	(0.010)	(0.006)	(0.115)	(0.011)
Return$_{i,t-11\rightarrow t-1}$÷ 100	0.007**	0.007**	0.015**	0.021**	0.011*	0.122*	0.017*
	(0.002)	(0.002)	(0.005)	(0.007)	(0.004)	(0.052)	(0.008)
Return$_{i,t}$÷ 100	-0.012	-0.012	0.029	0.063	-0.023	0.449*	0.191**
	(0.008)	(0.008)	(0.023)	(0.032)	(0.029)	(0.191)	(0.027)
Return$_{i,t+1}$÷ 100	-0.170**	-0.170**	0.009	0.053	-0.226**	1.521**	0.098**
	(0.016)	(0.016)	(0.020)	(0.047)	(0.023)	(0.217)	(0.024)
Δlog(Institutional Ownership$_{i,t}$)	-0.001*	-0.001*	-0.005*	0.009**	-0.002	0.001	0.129**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.027)	(0.005)
Prior quarter turnover$_{i,t}$	0.005**	0.005**	-0.005	0.005	0.001	0.007	0.011*
	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.040)	(0.005)
Liquidity ratio$_{i,t}$	0.001	0.001	0.005	-0.013	-0.014	-0.071	0.128**
	(0.003)	(0.003)	(0.017)	(0.021)	(0.022)	(0.090)	(0.023)
Years since IPO$_{i,t}$	-0.001*	-0.001*	0.001	0.001	0.000	0.006	-0.002
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.010)	(0.001)
Constant	0.028	0.028	0.038	0.097	0.059	-0.040	-0.275**
	(0.017)	(0.017)	(0.045)	(0.056)	(0.040)	(0.501)	(0.054)
# months	136	136	136	136	136	136	136
Average R^2	0.321	0.321	0.157	0.181	0.222	0.172	0.235

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

Table 9. Predicting monthly market returns using aggregate monthly breadth changes

The dependent regression variable is month t + 1's aggregate Shanghai/Shenzhen stock market return in excess of the riskfree return. Depending on the column and panel, the explanatory variable $\Delta\overline{\text{Breadth}}_t$ denotes the across-stock average equal-weighted or wealth-weighted breadth change among all, retail, or institutional investors. $\text{Return}_{m,t}$ is the Chinese stock market return in month t. The variable $\Delta\log(\overline{\text{IO}}_t)$ is the change from month-end $t - 1$ to month-end t in the log fraction of the SSE tradable A-share market capitalization owned by institutions. Newey-West (1987) standard errors with one lag are in parentheses.

	Equal-weighted		Wealth-weighted	
Panel A: Total breadth change				
$\Delta\overline{\text{Breadth}}_t$	-27.170	-27.366	-23.646**	-23.616**
	(18.462)	(23.871)	(6.790)	(6.014)
$\text{Return}_{m,t}$		0.169		0.054
		(0.099)		(0.086)
$\Delta\log(\overline{\text{IO}}_t)$		1.150		11.108
		(15.005)		(11.095)
Constant	2.217**	1.882*	0.219	0.139
	(0.846)	(0.730)	(0.829)	(0.789)
N	137	137	137	137
R^2	0.018	0.047	0.099	0.122
Panel B: Retail breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\overline{\text{Breadth}}_t$	-27.131	-27.330	-25.532**	-22.191*
	(18.457)	(23.870)	(9.301)	(9.421)
$\text{Return}_{m,t}$		0.169		0.116
		(0.099)		(0.091)
$\Delta\log(\overline{\text{IO}}_t)$		1.154		3.731
		(15.007)		(12.269)
Constant	2.217**	1.882*	0.826	0.753
	(0.846)	(0.730)	(0.830)	(0.825)
N	137	137	137	137
R^2	0.018	0.047	0.061	0.076
Panel C: Institutional breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\overline{\text{Breadth}}_t$	-18.295*	-18.850	-0.420	-1.145
	(8.772)	(12.419)	(0.802)	(1.220)
$\text{Return}_{m,t}$		0.091		0.119
		(0.111)		(0.096)
$\Delta\log(\overline{\text{IO}}_t)$		11.357		13.185
		(12.508)		(14.494)
Constant	1.507	1.337	1.854*	1.431
	(0.877)	(0.802)	(0.870)	(0.755)
N	137	137	137	137
R^2	0.028	0.057	0.002	0.040

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

Table 10. Predicting market return skewness using aggregate monthly breadth changes

The dependent regression variable is the skewness of the aggregate Shanghai/Shenzhen stock market daily returns during month $t + 1$. Depending on the column and panel, the explanatory variable $\Delta\overline{\text{Breadth}}_t$ denotes the across-stock average equal-weighted or wealth-weighted breadth change among all, retail, or institutional investors. $\text{Return}_{m,t}$ is the Chinese stock market return in month t. The variable $\Delta\log(\overline{\text{IO}}_t)$ is the change from month-end $t-1$ to month-end t in the log fraction of the SSE tradable A-share market capitalization owned by institutions. Newey-West (1987) standard errors with one lag are in parentheses.

Panel A: Total breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\overline{\text{Breadth}}_t$	-2.296	-2.595	1.359**	0.727
	(1.405)	(1.633)	(0.511)	(0.572)
$\text{Return}_{m,t}$		-0.030**		-0.029**
		(0.007)		(0.008)
$\Delta\log(\overline{\text{IO}}_t)$		-0.489		-0.061
		(0.525)		(0.405)
Constant	-0.075	-0.012	0.006	0.017
	(0.083)	(0.081)	(0.100)	(0.096)
N	137	137	137	137
R^2	0.014	0.115	0.034	0.111
Panel B: Retail breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\overline{\text{Breadth}}_t$	-2.297	-2.596	1.145	0.541
	(1.405)	(1.633)	(0.672)	(0.903)
$\text{Return}_{m,t}$		-0.030**		-0.031**
		(0.007)		(0.008)
$\Delta\log(\overline{\text{IO}}_t)$		-0.489		0.145
		(0.525)		(0.398)
Constant	-0.075	-0.012	-0.043	-0.008
	(0.083)	(0.081)	(0.098)	(0.094)
N	137	137	137	137
R^2	0.014	0.115	0.013	0.105
Panel C: Institutional breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\overline{\text{Breadth}}_t$	0.723	-0.560	0.040	-0.082
	(0.601)	(0.742)	(0.060)	(0.100)
$\text{Return}_{m,t}$		-0.034**		-0.034**
		(0.009)		(0.008)
$\Delta\log(\overline{\text{IO}}_t)$		0.195		0.509
		(0.440)		(0.661)
Constant	-0.076	-0.041	-0.083	-0.049
	(0.089)	(0.083)	(0.090)	(0.088)
N	137	137	137	137
R^2	0.004	0.105	0.002	0.106

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

Table 11. Correlates of aggregate monthly breadth changes

Depending on the column, the dependent regression variable is the across-stock average equal-weighted or wealth-weighted breadth change among all, retail, or institutional investors at time $t + 1$. The explanatory variable $\Delta\overline{\text{Breadth}}_t$, which is the lag of the dependent variable, similarly depends on the column. $\text{Return}_{m,t}$ is the Shanghai/Shenzhen stock market return in month t. The variable $\Delta\log(\overline{\text{IO}}_t)$ is the change from month-end t – 1 to month-end t in the log fraction of the SSE tradable A-share market capitalization owned by institutions. Newey-West (1987) standard errors with one lag are in parentheses.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
$\Delta\overline{\text{Breadth}}_t$	0.365	0.364	0.031	0.202	0.382**	-0.065
	(0.203)	(0.203)	(0.105)	(0.119)	(0.146)	(0.121)
$\text{Return}_{m,t+1}$	0.027	0.027	-0.282*	-0.235	-0.086	-1.715
	(0.046)	(0.046)	(0.138)	(0.169)	(0.137)	(1.143)
$\text{Return}_{m,t}$	0.089	0.089	-0.034	-0.371**	-0.177*	-2.276*
	(0.070)	(0.070)	(0.091)	(0.126)	(0.085)	(1.103)
$\Delta\log(\overline{\text{IO}}_t)$	0.036	0.036	-0.055	-0.102	0.139	-1.466
	(0.034)	(0.034)	(0.061)	(0.104)	(0.093)	(1.450)
Constant	0.004	0.004	-0.019**	-0.048**	-0.023**	-0.246**
	(0.003)	(0.003)	(0.006)	(0.010)	(0.005)	(0.069)
N	136	136	136	136	136	136
R^2	0.151	0.151	0.115	0.234	0.228	0.159

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

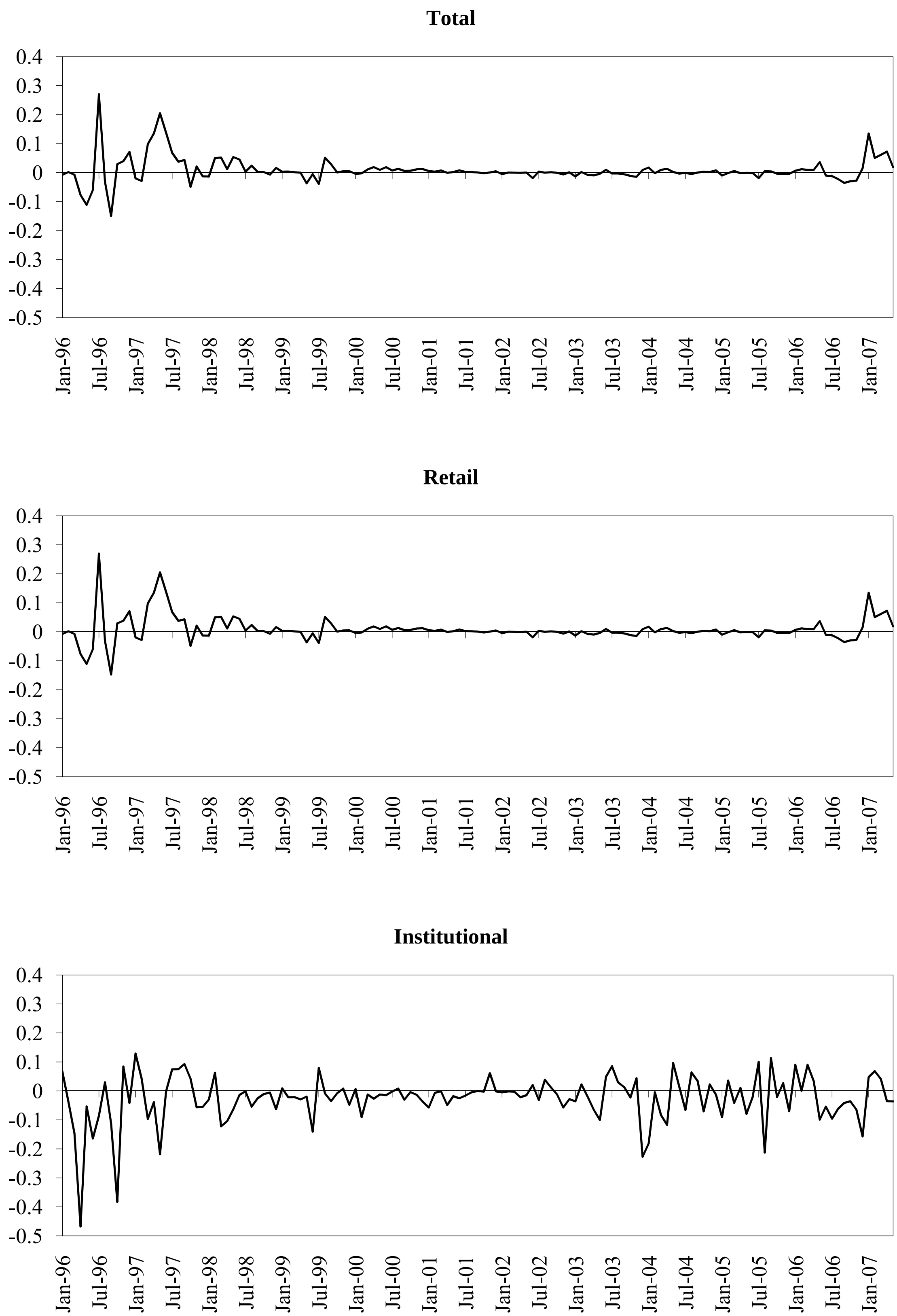

Figure 1. Average equal-weighted breadth change monthly time series

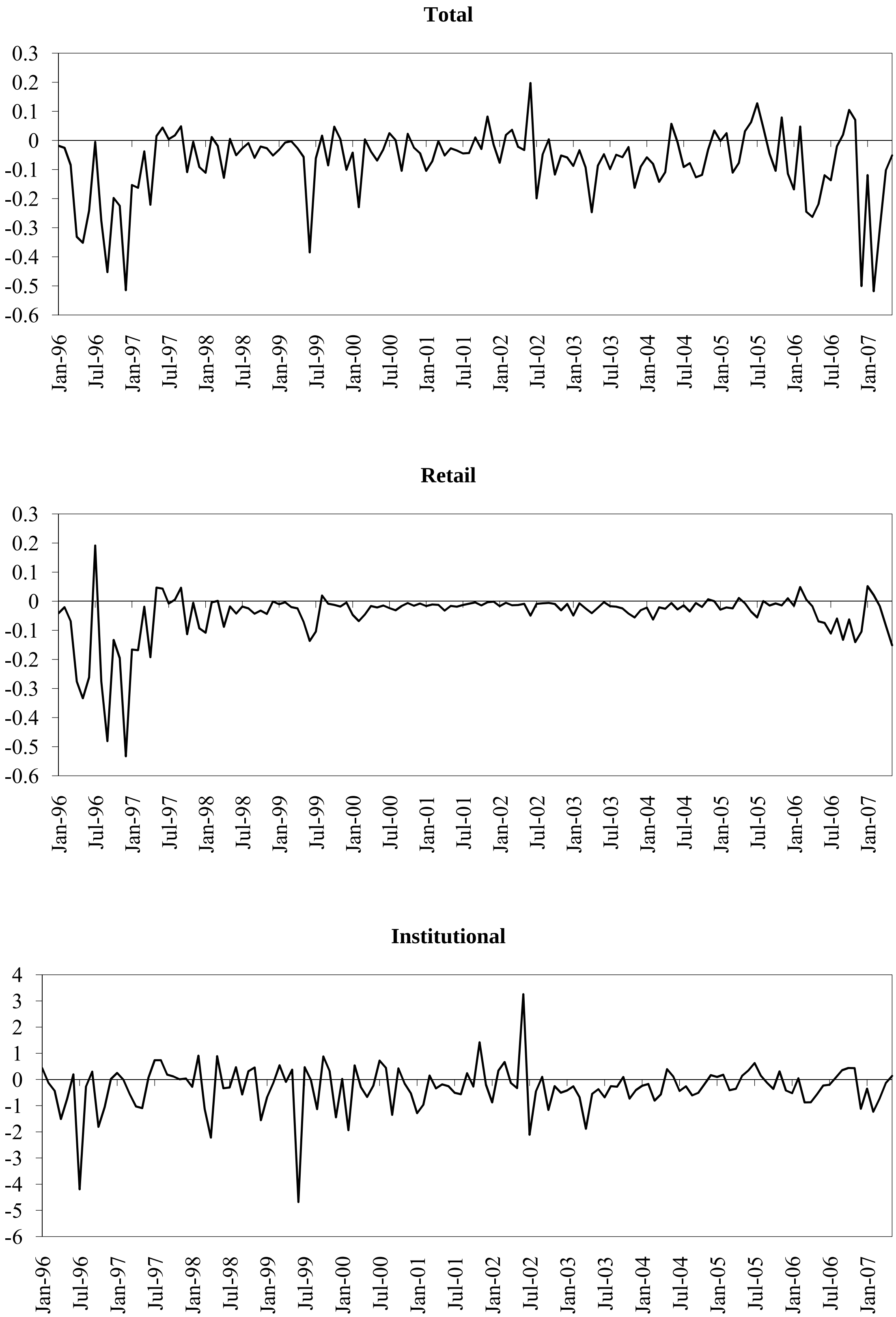

Figure 2. Average wealth-weighted breadth change monthly time series