Does Ownership Breadth Predict Stock Returns? New Evidence from Market-Wide Holdings Data*

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Abstract

We test how ownership breadth predicts stock returns. Using holdings data on a representative Shanghai Stock Exchange investor sample from 1996 to 2007, we find that cross-sectionally, high breadth change quintile stocks underperform low breadth change quintile stocks by 22 percent per year, a result driven by retail investor ownership breadth. This is consistent with breadth increases primarily reflecting greater popularity among noise traders rather than the easing of short-sales constraints. In the time series, high average ownership breadth changes across stocks predict a low Chinese stock market return in the next month, and may predict higher market return skewness.

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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) were the first to propose using ownership breadth as a return predictor, inspired by the Miller (1977) model of how the interaction of heterogeneous investor beliefs and short-sales constraints affects prices. CHS's insight is that when relatively few investors hold a stock long, this may signal that there are many investors with bad news about the stock who would like to but cannot short it due to short-sales constraints. These sidelined investors' bad news is not incorporated into the stock's price, resulting in low future returns.[1]

Although the use of ownership breadth as a measure of short-sales constraints is intuitively appealing, a proper empirical test of the CHS theory is challenging. Ownership breadth must be measured over the set of *all* investors subject to short-sales constraints while excluding any investors who are not subject to short-sales constraints. The inability to do this may explain why empirical support for the theory has been mixed to date. CHS are able to observe ownership breadth only among mutual funds. Short-selling is rare among mutual funds, but many other investors in the market are similarly constrained, so an ownership breadth increase among mutual funds does not necessarily imply an ownership breadth increase among all investors who are prohibited from short-selling. CHS find that cross-sectionally, stocks with mutual fund ownership breadth decreases 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.

We use a new holdings dataset from the Shanghai Stock Exchange (SSE) that allows us to conduct a proper test of the CHS theory. The investors in the data are a random, survivorship-bias-free sample of all SSE investors. At the end of each trading day from January 1996 to May

[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 also exceptions. For example, Diamond and Verrecchia (1987) argue that short sale constraints do not bias stock prices on average when investors correctly anticipate that pessimistic investors are sitting on the sidelines. More recently, Bai, Chang, and Wang (2006) show that, depending on the relative importance of informed versus uninformed trading motives, short sale constraints can increase, decrease, or have no impact on stock prices.

2007, the source data records each investor's complete SSE A-share holdings.[2] We obtain aggregated ownership breadth change measures for each stock from this investor-level data. Short-selling is prohibited in the Chinese stock market. This is useful for two reasons. First, it means that when we calculate breadth change over all investors in the market, we are measuring it over the theoretically appropriate universe: all investors unable to sell short without including any investors who are able to sell short. Second, the blanket prohibition on short-selling increases the power of our tests of the CHS theory, since the theoretical relationship between breadth and future returns is attenuated as more investors can sell short.

The CHS theory makes no distinction between the cross-section and time-series of stock returns; decreased ownership breadth should predict low returns along both dimensions. Whereas the prior literature has restricted its attention to cross-sectional tests, the high frequency of our data allows us to conduct time-series tests as well.

Our cross-sectional findings contrast sharply with CHS. High breadth change stocks *underperform* low breadth change stocks. The annualized difference in the four-factor alpha between the lowest and highest quintiles of breadth change is 22 percent, with a *t*-statistic of 8.8. One possible interpretation of this finding is that breadth increases primarily reflect greater popularity among noise traders, which causes overvaluation, rather than the easing of short-sales constraints. Two additional results are consistent with this interpretation.

First, based on the intuition that wealthy investors are less likely to be noise traders, we redefine breadth change so that investors are weighted by their prior month's stock market wealth instead of being weighted equally. De-emphasizing small investors using this definition, the annualized four-factor alpha difference between the low and high breadth change portfolios falls to 5 percent.

Second, we calculate breadth changes only among institutions, which seem less likely than individuals to be noise traders. 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 wealth-weighted institutional breadth change replicate the original CHS result: high institutional breadth change stocks outperform low institutional breadth change stocks. The annualized difference in the four-factor alphas is 9 percent, with a t-statistic

[2] A shares, which were restricted to domestic investors until 2003, dominate the SSE. For example, at year-end 2007, A shares constituted over 99 percent of SSE market capitalization.

of 2.7. This suggests that in the cross-section, the CHS theory is a reasonable description of interactions among investors with valid signals about fundamental stock values. CHS do not model noise traders who observe no valid signals, so the theories break down when ownership breadth statistics include a large fraction of noise traders.

The institutional breadth change findings indicate that the negative relationship between total breadth changes and future returns comes entirely from retail investor breadth changes. The predictive ability of retail investor 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 their IPO. It continues to predict returns up to five months after portfolio formation. It survives controls for size, book-to-market, momentum, turnover, stock age, change in the fraction of shares owned by institutions, and the shadow cost of incomplete information as formulated by Merton (1987) and empirically analyzed by Bodnaruk and Ostberg (2009).

The predictive power of institutional breadth change is less robust. 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 formation. It survives controls for size, book-to-market, momentum, turnover, stock age, and change in the fraction of shares owned by institutions, but additionally controlling for the shadow cost of incomplete information eliminates its significance.

In our time-series tests, we use the value-weighted average of breadth changes across stocks within a single time period as our predictive variable. Our findings are again contrary to CHS: high average breadth change this month predicts *low* Chinese stock market returns next month. Somewhat puzzlingly, this negative predictive power is statistically significant only for the average of wealth-weighted breadth changes, not for the average of equal-weighted breadth changes. This appears to be driven by retail breadth changes: the average of wealth-weighted retail breadth changes is a significant negative predictor, but the average of equal-weighted retail breadth changes is not. Among institutions, the average wealth-weighted breadth change is not a significant predictor, but there is some evidence that the average equal-weighted breadth change is a contrarian signal.

We repeat the time-series tests at the daily frequency but do not find robust evidence that daily market returns are predicted by breadth changes during the prior five days.

Our last piece of analysis examines whether the average ownership breadth change predicts the skewness of aggregate market returns. The model of Hong and Stein (2003) suggests that large market crashes should be preceded by narrowing ownership breadth due to a mechanism similar to that in CHS: narrowing ownership breadth signals that bad news is being excluded from market prices due to short-sales constraints. In a univariate regression, the average wealth-weighted breadth change among all investors during month t positively predicts the skewness of daily returns during month $t + 1$, which is consistent with Hong and Stein (2003). However, the significance of this result is not robust to additionally controlling for the month t market return and 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.[3] In addition, our paper is related to others that seek to identify the impact individual investors have on prices and whether institutional investors have better portfolio performance than individuals.[4]

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

I. Data Description

The ownership breadth measures used in the empirical analysis are aggregated at the Shanghai Stock Exchange into stock- or market-level measures, using the individual account data maintained by the Shanghai Stock Exchange. The aggregation is carried out under arrangements that maintain strict confidentiality requirements to ensure that no individual account data is disclosed.

The Shanghai Stock Exchange and the Shenzhen Stock Exchange are the two stock exchanges in China. At the end of 2007, the 860 stocks traded on the Shanghai Stock Exchange

[3] These studies have adopted a number of proxies to measure short-sale 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)).

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

had a total market capitalization of $3.7 trillion, making it Asia's second-largest stock exchange by market capitalization (behind the Tokyo Stock Exchange). To trade on the exchange, investors—whether they are individual investors or institutions—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 are not allowed to have multiple accounts.

The individual account data assembled by the Exchange for this project consists of a representative random sample of all accounts that were open at the end of May 2007.[5] Detailed account-level data at the daily frequency were used to generate aggregate statistics at the stock or market level from January 1996 to May 2007, which are then used for statistical analysis in this paper. Since this sample contains both currently active and inactive accounts, we are able to include currently inactive investors in our aggregate statistics, so there is no survivorship bias.

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

II. Main Variable Definitions

Following CHS, we define the equal-weighted total ownership breadth change of stock *i* at time *t* in the following way. We first restrict the sample to investors who have a long position in at least one SSE stock at both t and $t - 1$. This restriction ensures that the breadth change measure captures only 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 $t - 1$ and t in the fraction of these subsample investors who own stock *i*. We also further restrict the investor subsample to retail investors or institutional investors to obtain equal-weighted retail breadth change and equal-weighted institutional breadth change. For most of our analyses, the unit of *t* will be a month, but sometimes, we will use daily breadth changes where the units of *t* will be a day.

Equal-weighted ownership breadth change does not make distinctions between institutions with large amounts of money under management and retail investors with modest

[5] The Exchange extracted all account information from a randomly selected sample of all individual 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 individual 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 individual 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.

personal assets. Wealthy investors may have more resources to gather information, which would cause their stock ownership decision to be more informative than that of smaller investors.[6] We thus additionally use an alternative measure of ownership breadth not found in CHS. 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 both t and $t - 1$. Wealth-weighted ownership breadth change is the difference in the $t - 1$ stock market wealth of subsample investors who hold i at t and subsample investors who hold i at $t - 1$, all divided by the $t - 1$ stock market wealth of all subsample investors. Wealth-weighted retail breadth change and wealth-weighted institutional breadth change are defined analogously over their respective investor populations.

Our cross-sectional analysis involves evaluating the performance of portfolios formed on breadth changes. We estimate four-factor alphas, where the factor portfolio returns capture size, value, and momentum effects. The market portfolio return is the composite Shanghai and Shenzhen market return, weighted by tradable market capitalization.[7] 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), using the entire Chinese stock market to calculate percentile breakpoints. We form SMB based on tradable market capitalization, and HML based on the ratio of book equity to total market capitalization.[8] We construct the momentum factor portfolio MOM following the methodology described on Kenneth French's website. Specifically, at the end of month $t - 1$, we calculate the 50th percentile tradable market capitalization (in the entire Chinese market) at month-end $t - 1$ and the 30th and 70th percentile stock returns over month-ends $t - 12$ to $t - 2$. The intersections of these breakpoints delineate six tradable market capitalization weighted portfolios for which we compute month t returns. MOM is the equally-weighted average return on the two high prior return portfolios minus the equally-weighted average return on the two low prior return portfolios.

[6] 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.

[7] At year-end 2007, 72% of A-share market capitalization was non-tradable. These shares have the same voting and cashflow rights as tradable shares, and are typically owned directly by the Chinese government or domestic financial institutions owned by the government.

[8] 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.

III. Cross-Sectional Results

A. Main Portfolio-Based 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 first 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. To form the "Quintile n" portfolio, we equally weight across the size quintiles the five nth quintile breadth change sub-portfolios, and hold the stocks for one month before re-forming the portfolios at the end of month $t + 1$.

The top half of Table 1 presents summary statistics on equal-weighted breadth changes by size quintile. There is no average trend in equal-weighted total breadth change. Recall that breadth change is calculated only among investors who had a long position in the market in both the current and prior month, so the breadth change statistics are mostly unaffected by the tremendous increase in Chinese market participation during our sample period. The volatility of breadth change increases with firm size, which is why we and CHS form breadth-change portfolios within size quintiles; otherwise, the extreme quintiles of breadth change would be dominated by large firms. The summary statistics for equal-weighted retail breadth change are nearly identical to equal-weighted total breadth change, since retail investors vastly outnumber institutions, and this breadth change measure gives the same weight to an individual as an institution. Equal-weighted institutional breadth change has a small negative trend and is more volatile than retail breadth change.

The bottom half of Table 1 shows summary statistics for wealth-weighted breadth changes. There is a more pronounced negative trend for wealth-weighted breadth changes for both individuals and institutions; the trend is stronger for institutions. Wealth-weighted institutional breadth change is more volatile than wealth-weighted retail breadth change, and each wealth-weighted breadth change measure is more volatile than its equal-weighted counterpart. Because institutions have disproportionately large stock holdings, total breadth changes do not hew as closely to retail breadth changes when we wealth-weight rather than equal-weight.

Table 2 shows raw returns and alphas for the breadth change portfolios. 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 197 basis points per month, or 23.6% per year, with a t-statistic of 9.4. This return differential barely falls to 23.3% per year when we adjust for CAPM beta risk, and to 22.2% per year with a t-statistic of 8.8 when we additionally adjust for size, value, and momentum effects. Abnormal returns come not only from negative alphas in the highest breadth change portfolio (which cannot be shorted), but also the lowest breadth change portfolio, which has a significant positive four-factor alpha of 14.6% per year. These results are contrary to the CHS model, which predicts that future returns are *increasing* in ownership breadth, since high breadth means fewer investors with bad news are sitting on the sidelines. Instead, the results appear consistent with stocks becoming overvalued when they gain popularity among noise traders and undervalued when they lose popularity.

The right half of Table 2, Panel A provides evidence supportive of the noise trader story. Wealthy investors may be less likely to be noise traders because they have greater resources with which to gather information. If so, 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, or 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 annualized alphas: 5.4% and 5.3%, respectively.

Further evidence in favor of the noise trader story comes from Panels B and C of Table 2, which show returns from portfolios formed from sorts on retail or institutional investor breadth changes. In panel B, parallel to those sorts on the total breadth changes, we sort stocks into five quintiles based on the retail breadth changes. For the analysis based on institutional breadth changes in Panel C, however, due to the fact that a large number of stocks every month have zero breadth change, our institutional breadth change breakpoints are the 10th and 90th percentiles instead of at the 20th, 40th, 60th, and 80th percentiles.

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 that stocks experiencing large equal-weighted institutional breadth increases do not underperform stocks experiencing large equal-weighted institutional breadth decreases; the difference is insignificant. The relationship between equal-weighted total breadth changes and future returns in Panel A is entirely driven by equal-weighted retail breadth changes. The returns of portfolios formed on equal-weighted retail breadth changes are almost identical to those of portfolios formed on equal-weighted total breadth changes.

Moving to wealth-weighted breadth changes, we find that even among individuals, forming portfolios based on wealth-weighted breadth changes decreases the spread between the high- and low-breadth-change portfolios. The four-factor alpha of the difference between the lowest and highest wealth-weighted retail breadth change portfolios is 16.6% per year, which is smaller than the 22.1% per year difference between the lowest and high equal-weighted retail breadth change portfolios.

Among institutions, wealth-weighting breadth causes us to replicate the CHS empirical result: high wealth-weighted institutional breadth change stocks significantly outperform low wealth-weighted institutional breadth changes stocks by 7.3%, 7.4%, and 8.5% per year on a raw, one-factor-adjusted, and four-factor-adjusted basis, respectively. The reason wealth-weighted institutional breadth changes are so different from equal-weighted institutional breadth changes is that there are many institutions who own 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 of the identities of the institutions in our data, we suspect that these small institutional portfolios are held by non-financial companies that do not employ professional portfolio managers and thus behave more like noise traders.

B. Persistence of Portfolio-Based Results

Although both retail and institutional breadth changes predict returns, only retail breadth change appears to significantly predict returns beyond one month into the future.

To assess 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 weight stocks by $t + n - 1$ tradable market capitalization within each size × breadth change sub-portfolio.

We then calculate the return of the equal-weighted portfolio of all the highest breadth change sub-portfolios across the market cap quintiles minus the return of the equal-weighted portfolio of all the lowest breadth change sub-portfolios across market cap quintiles during month $t + n$. We repeat this procedure each month to produce a "$t + n$" return difference series.

Table 3 shows the return differences 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 high and low breadth change portfolio alphas is still –4.6% per year. 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 shows only slightly weaker predictive persistence; the difference between the alphas of portfolios sorted on wealth-weighted retail breadth stops being significant at month $t + 4$. 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 always predicts a larger spread than wealth-weighted retail breadth, consistent with our results in Table 2 based on t+1 returns.

In contrast, institutional breadth change does not significantly predict returns beyond one month, whether breadth changes are equal- or wealth-weighted. None of the alpha differences in Table 3 under the institutional columns is significant.

As in Table 2, the predictive power of total breadth change beyond the first month is driven by retail breadth change. The alpha differences between the high and low equal-weighted total breadth change portfolios are almost the same as those between the high and low equal-weighted retail breadth change portfolios. The alpha gap beyond the first month disappears for portfolios formed on wealth-weighted total breadth change, where institutional breadth change plays a more prominent role.

C. Robustness of Portfolio-Based 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 stocks that are less than one year removed from their IPO. The motivation for this exclusion is that stocks may systematically experience breadth increases for some time after their IPO, as lock-ups expire and the investor population becomes more familiar with the company. In the U.S. market, IPO stocks generally have low returns following their first day of trading (Ritter, 1991). Therefore, including recent-IPO stocks in our sample may cause us to confound post-IPO underperformance with a breadth change effect.

Table 4 shows, for each subsample, the highest breadth change quintile four-factor alpha minus the lowest breadth change quintile four-factor alpha in the first month after stocks are sorted by breadth change. The retail breadth change results, whether equal-weighted or wealth-weighted, are robust in all subsamples. Unlike many return anomalies documented in the literature, the predictive power of retail breadth change is somewhat stronger among large stocks than small stocks. Excluding recent IPOs has no effect on the results. Interestingly, the magnitude of the alpha spread in the first half of the sample is significantly larger than that in the second half. This could be consistent with increasing sophistication of retail investors over time, or increasing sophistication of institutional investors over time in betting against retail investors.

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 to not 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 6.4% per year but insignificant, whereas in the second half, it is 11.9% per year and highly significant. Wealth-weighted institutional breadth also significantly predicts returns only among large stocks (alpha spread of 20.3%), not small stocks (insignificant alpha spread of 3.8%). These differences could be due to the increase in sophistication among institutions over time, and the fact that foreign institutions, which may be more sophisticated, were allowed to enter the SSE since 2003, and that financial institutions tend to focus their attention on large stocks. The wealth-weighted institutional breadth change results are not affected, however, by excluding recent IPOs.

D. Fama-MacBeth Tests

Although our portfolio tests have controlled for size, value, and momentum effects, there are other predictors of cross-sectional returns that have been documented in the literature. In order to control for these additional known predictors, we run Fama-MacBeth (1973) regressions of stock returns on the stock's breadth change, log of tradable market capitalization, book-to-market ratio, prior year return, prior quarter turnover, change in log institutional ownership during the prior month, and shadow cost of incomplete information as derived in Merton (1987). This last variable captures abnormal returns due to the Merton (1987) "investor recognition hypothesis," where information constraints cause investors to neglect holding certain stocks. The investors who do hold these neglected stocks sacrifice diversification and hence demand a higher expected return as compensation. Clearly, investor recognition is closely related to ownership breadth and so should be controlled for when testing the pricing implications of ownership breadth changes. We use the control variable λ used by Bodnaruk and Ostberg (2009) to test the investor recognition hypothesis in Swedish data:

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

where 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 market capitalization as a fraction of total Chinese tradable market capitalization at month-end t; and M_{it} is stock i's total breadth level at month-end t, i.e. 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.

Table 5 shows that, consistent with our earlier portfolio-based tests, both retail breadth change measures remain highly significant negative predictors of future returns. A one standard deviation increase in equal-weighted retail breadth reduces next month's return by 12.277 × 0.061 = 0.75% per month, or 9.0% per year, and a corresponding increase in wealth-weighted retail breadth reduces next month's return by 4.388 × 0.133 = 0.58% per month, or 7.0% per year. In contrast, neither institutional breadth change measure is significant. The loss of significance on wealth-weighted institutional breadth change is caused by controlling for λ. We also see that the coefficient on prior quarter turnover is significantly negative across all specifications. This is consistent with the U.S. evidence as documented in Hong and Stein (2007), who interpret high trading volume as an indicator of high investor sentiment.

E. Cross-sectional Predictors of Breadth Change

We analyze the predictors of breadth change by running Fama-MacBeth regressions of the breadth change during month t on explanatory variables defined as of month $t-1$. These explanatory variables are the change in log institutional ownership, the log of tradable market capitalization, the book-to-market ratio, the prior-year return, the prior quarter turnover, and the number of years since the firm's IPO.

Table 6 shows that the most consistent predictor of breadth increases is prior-year return, which has a significant positive coefficient for all breadth measures. Change in institutional ownership negatively predicts equal-weighted retail and institutional breadth change, but does not predict the corresponding wealth-weighted measures. Stock size negatively predicts both institutional breadth change measures, as well as wealth-weighted retail breadth. Being a value stock is associated with lower equal-weighted and wealth-weighed retail breadth changes. Prior quarter turnover predicts future equal-weighted breadth increases. Notably, years since IPO does not predict any of the breadth change measures.

IV. Time-Series Results

A. Aggregate Breadth Change: Definitions and Summary Statistics

We define monthly aggregate breadth change as 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. We will also analyze daily aggregate breadth change, which is the average breadth change of all SSE stocks during a trading day, weighted by each stock's tradable market capitalization at the end of the prior trading day.

The motivation for these aggregate measures is simple. The CHS model makes no distinction between the cross-sectional and time-series dimensions. Therefore, if high breadth change predicts high returns in the cross-section, then when the average breadth change across stocks in a given time period is high, aggregate market returns should be high next period.

Table 7 reports summary statistics for aggregate monthly and daily breadth change. The institutional breadth change measures are substantially more volatile than the retail breadth change measures. For example, at the monthly frequency, equal-weighted institutional breadth change is almost twice as volatile as equal-weighted retail breadth change, and wealth-weighted institutional breadth change is more than ten times as volatile as the wealth-weighted retail breadth change. The retail breadth change measures exhibit substantially more autocorrelation than the institutional breadth change measures. The equal-weighted monthly retail breadth change, for example, has an autocorrelation of 0.322, whereas equal-weighted monthly institutional breadth change's autocorrelation is only 0.076.[9]

The time series of monthly equal- and wealth-weighted aggregate 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 the institutional breadth change remains relatively high throughout our sample period.

B. Predicting Expected Monthly Market Returns

To test the time-series prediction of the CHS model, we run regressions of the aggregate Chinese market excess return on lagged average breadth change. In a second specification, we also control for the previous period's market return and the change in log percent of SSE tradable market capitalization owned by institutions. Panel A of Table 8 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 $23.49 \times 0.120 = 2.8\%$ lower market return next month in the univariate regression. This is again contrary to the CHS model prediction, but is consistent with the cross-sectional evidence that an increase in breadth change leads to lower subsequent returns. One possible interpretation is that a high average ownership breadth increase indicates that investors have become overly excited about stocks.

Given the stronger predictive power of equal-weighted total breadth in the cross-section, it is somewhat surprising that the coefficient on equal-weighted average total breadth change is insignificant, although it remains 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 8. The retail breadth change results are similar to the total breadth change results: higher average breadth changes leads to lower subsequent returns, but this effect is significant only for the average wealth-weighted retail breadth change. Average institutional breadth change

[9] 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. A future draft of this paper will correct for any such finite-sample bias.

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 $-18.424 \times 0.082 =$ 1.51% lower market return next month. Again, it is somewhat surprising in light of the cross-sectional results that average wealth-weighted institutional breadth change does not positively predict future returns.

C. Correlates of Aggregate Monthly Breadth Changes

To find the predictors of aggregate monthly breadth change, we regress the various measures on their own lag, the lagged market return, and the lagged change in log percent of SSE tradable market capitalization owned by institutions. We also estimate aggregate monthly breadth change's relationship with the contemporaneous market return and log aggregate institutional ownership percentage change.

The results are contained in Table 8. Panel A shows that average equal-weighted total breadth change is not significantly predicted by its own lag, lagged market return, and lagged log aggregate institutional ownership percentage change. However, average wealth-weighted total breadth change is positively predicted by its own lag and negatively predicted by the lagged market return. Panels B and C show that the positive coefficient on wealth-weighted total breadth change's lag is driven by retail investors, whereas the negative coefficient on lagged market return is present among both retail and institutional investors.

Turning to the contemporaneous relationship, we find that average equal-weighted total breadth change has no relationship with the contemporaneous market return, but is negatively correlated with the contemporaneous change in institutional ownership. The model of Hong and Stein (2003) suggests that market crashes stop when previously sidelined investors step in to provide buying support. Therefore, the lack of a contemporaneous correlation between average equal-weighted breadth change and market returns may be inconsistent with the model. However, average wealth-weighted total breadth change has the appropriate contemporaneous relationship with market return: when the market goes down, breadth change increases significantly. Looking at each investor subpopulation separately, we see that this negative relationship is driven mostly by institutional investors.

D. Predicting Daily Market Returns

In this subsection, we perform an analysis parallel to that in Section IV.B, but at the daily frequency. We regress daily market returns on breadth changes during each of the prior five days. In a second specification, we also control for market returns and the change in log institutional ownership percentage of SSE tradable market capitalization in each of the prior five days. As illustrated in Panels A through C of Table 9, the five lagged coefficients on breadth change are generally insignificant. The third lag of wealth-weighted retail breadth change is significantly positive in both regression specifications, but this finding is hard to interpret, since none of the other five days' coefficients are significant, and some of them are negative. There is no obvious economic mechanism that would cause breadth change to predict returns only three days ahead, leading us to suspect that this positive relationship is spurious.

E. Correlates of Aggregate Daily Breadth Changes

What determines breadth change at a daily frequency? Panel A of Table 9 shows that both average total breadth measures are positively predicted by their own lags and market returns in the prior five days. There is no clear pattern in the coefficients on lagged change in log aggregate institutional ownership percentage. Panel B shows that average retail breadth change has a similar relationship to the lagged control variables. On the other hand, we see in Panel C that average institutional breadth changes is not significantly predicted by their own lags, and the equal-weighted measure has a tendency to be negatively predicted by the past five days of returns.

Contemporaneously, average equal-weighted total breadth change is negatively correlated with market returns and change in log aggregate institutional ownership percentage. The relationship with market return disappears for the wealth-weighted measure, which is also positively correlated with change in log aggregate institutional ownership percentage. Retail investors tend to decrease breadth on days with high market returns and aggregate institutional ownership increases. Average equal-weighted institutional breadth change has a positive relationship with contemporaneous market returns, but there is no such relationship for wealth-weighted institutional breadth change. Both institutional breadth change measures are positively correlated with contemporaneous change in log aggregate institutional ownership percentage.

F. Predicting Market Return Skewness

Our final set of tests is motivated by insights from the Hong and Stein (2003) model, which is closely related to the CHS model. Hong and Stein (2003) argue that when investors exit the market due to short-sales constraints, large market crashes are more likely because stock prices fail to reflect the negative news held by the constrained investors. When a small shock causes optimistic unconstrained stock holders to sell, the previously hidden negative news becomes incorporated into prices as market participants observe at which point the pessimistic investors jump back into the market. If the pessimistic investors do not provide buying support at prices that are modestly lower than before the shock, market participants learn that the previously sidelined news was quite bad, leading to a crash.

We test this story by regressing daily market return skewness during the next month on the average change in breadth during the current month. Hong and Stein (2003) predict 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 measure is significantly positive, consistent with Hong and Stein (2003). However, this relationship is not robust to including controls for the prior month's market return and change in log aggregate institutional ownership percentage. Panels B and C show that none of the retail and institutional breadth change measures significantly 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 turnover and future skewness is also found in U.S. data (Chen, Hong, and Stein (2001)).

V. Conclusion

We have tested the ability of ownership breadth changes to predict stock returns in both the cross-section and the time-series. Our motivation is the theory of Chen, Hong, and Stein (2001), which predicts that increasing ownership breadth should predict high future returns because it indicates that less bad news is being withheld from prices due to short-sales constraints. Our data are uniquely suited to testing the theory because they are a representative sample of the stock holdings of *all* investors subject to short-sales constraints and—by virtue of the blanket ban on short-selling in Chinese stock markets—exclude all investors not subject to short-sales constraints.

When we restrict our sample to institutional investors, we find cross-sectional support for the theory: the higher the percentage (on a wealth-weighted basis) of institutions that begin holding a stock in a given month, the higher the stock's return the following month. This result is not, however, robust to controlling for the shadow cost of incomplete information arising from the Merton (1987) investor recognition hypothesis. When we include retail investors in our sample as well, the sign of the results flips in opposition to the theory: higher ownership breadth change predicts dramatically lower returns for the next five months. In the time series as well, higher average ownership breadth change across stocks in a given month generally predicts lower aggregate market returns during the next month.

These results suggest that the Chen, Hong, and Stein (2001) theory could be a reasonable description of the relationship between ownership breadth and future returns when ownership breadth is measured among the subset of investors that draw unbiased signals about fundamental stock values. But when ownership breadth measures include unsophisticated retail investors, increasing breadth seems to reflect irrational exuberance rather than the easing of short-sales constraints.

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Table 1. Summary statistics of cross-sectional breadth change quintiles

In order to calculate breadth change between month-ends $t - 1$ and t, we restrict the sample to investors who hold at least one long SSE stock position at the end of both months $t - 1$ and t. Equal-weighted total breadth change for stock i is the change between $t - 1$ and t in the number of investors in this restricted sample holding stock i, divided by the total number of investors in the restricted sample. Wealth-weighted total breadth change is the value of all SSE stocks held at t by investors in the restricted sample who held stock i at t, minus the value of all SSE stocks held at $t - 1$ by investors in the restricted sample who held stock i at $t - 1$, divided by the value of all SSE stocks held by all investors in the restricted sample at $t - 1$. Institutional and retail breadth changes are defined analogously on the retail or institutional subsample. Market cap portfolio sorts for month t are done based on tradable market caps as of the end of month $t - 1$. All time periods are pooled in calculating the means and standard deviations. Breadth changes are expressed as percentages, so that a 1 percent breadth change is coded as 1, not 0.01.

		(Smallest firms) Quintile 1	Quintile 2	Quintile 3	Quintile 4	(Largest firms) Quintile 5	All firms
ΔEqual-weighted	Mean	-0.002	-0.003	-0.002	0.000	0.006	0.000
total breadth	Std. dev.	0.018	0.027	0.038	0.053	0.115	0.061
ΔEqual-weighted	Mean	-0.003	-0.003	-0.002	0.000	0.006	0.000
retail breadth	Std. dev.	0.018	0.027	0.038	0.053	0.115	0.061
ΔEqual-weighted	Mean	-0.003	-0.007	-0.008	-0.008	-0.013	-0.008
institutional breadth	Std. dev.	0.103	0.130	0.168	0.201	0.357	0.212
ΔWealth-weighted	Mean	-0.013	-0.019	-0.022	-0.024	-0.051	-0.026
total breadth	Std. dev.	0.124	0.189	0.241	0.336	0.548	0.324
ΔWealth-weighted	Mean	-0.009	-0.013	-0.015	-0.018	-0.031	-0.017
retail breadth	Std. dev.	0.061	0.073	0.101	0.130	0.227	0.133
ΔWealth-weighted	Mean	-0.065	-0.083	-0.118	-0.100	-0.231	-0.120
institutional breadth	Std. dev.	1.514	2.362	2.339	2.933	3.756	2.694

Table 2. Monthly returns on breadth change portfolios

This table shows the raw return in excess of the riskfree rate, CAPM alpha, and 4-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" portfolio holds the Quintile 5 portfolio long and the Quintile 1 portfolio short. 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" portfolio holds the "> 90th percentile" portfolio long and the "< 10th percentile" portfolio short. The returns are expressed in percentages, so that a 1 percent return is 1, not 0.01. Standard errors are reported 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	2.97**	1.08**	1.22**	2.24**	0.41	0.60**
(lowest breadth change)	(0.76)	(0.27)	(0.20)	(0.73)	(0.25)	(0.18)
Quintile 2	2.46**	0.50	0.60**	2.26**	0.36	0.47**
	(0.78)	(0.27)	(0.18)	(0.76)	(0.26)	(0.17)
Quintile 3	1.96**	0.12	0.28	2.04**	0.13	0.26
	(0.74)	(0.26)	(0.17)	(0.78)	(0.30)	(0.18)
Quintile 4	1.89*	-0.01	0.14	1.80*	-0.09	0.05
	(0.76)	(0.26)	(0.19)	(0.76)	(0.27)	(0.18)
Quintile 5	1.00	-0.86**	-0.63**	1.87*	-0.04	0.16
(highest breadth change)	(0.75)	(0.26)	(0.19)	(0.76)	(0.23)	(0.18)
5 – 1	-1.97**	-1.94**	-1.85**	-0.36*	-0.45*	-0.44*
	(0.21)	(0.21)	(0.21)	(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	2.96**	1.08**	1.21**	2.67**	0.79**	0.98**
(lowest breadth change)	(0.76)	(0.27)	(0.20)	(0.75)	(0.25)	(0.20)
Quintile 2	2.51**	0.55*	0.65**	2.27**	0.37	0.47**
	(0.79)	(0.27)	(0.17)	(0.76)	(0.27)	(0.17)
Quintile 3	1.96**	0.14	0.31	2.01**	0.17	0.32
	(0.73)	(0.26)	(0.17)	(0.74)	(0.27)	(0.17)
Quintile 4	1.88*	0.00	0.14	1.95*	0.03	0.18
	(0.76)	(0.26)	(0.19)	(0.77)	(0.26)	(0.18)
Quintile 5	1.00	-0.86**	-0.63**	1.31	-0.59*	-0.40*
(highest breadth change)	(0.75)	(0.26)	(0.19)	(0.76)	(0.24)	(0.17)
5 – 1	-1.96**	-1.94**	-1.84**	-1.36**	-1.39**	-1.38**
	(0.21)	(0.22)	(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	2.37**	0.56	0.70*	1.97**	0.06	0.14
	(0.75)	(0.32)	(0.28)	(0.75)	(0.22)	(0.17)
10th to 90th percentiles	2.00**	0.11	0.27	1.95*	0.07	0.23
	(0.76)	(0.25)	(0.16)	(0.75)	(0.26)	(0.16)
> 90th percentile	2.06**	0.15	0.33	2.58**	0.69*	0.85**
	(0.76)	(0.25)	(0.20)	(0.76)	(0.26)	(0.23)
> 90th – < 10th	-0.31	-0.41	-0.36	0.61*	0.62*	0.71**
	(0.30)	(0.31)	(0.31)	(0.28)	(0.28)	(0.27)

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

Table 3. Persistence of breadth change long-short portfolio 4-factor alphas

This table shows the 4-factor alphas from zero-investment portfolios that are formed based on breadth change, 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 market cap quintiles and short an equal-weighted portfolio of all the lowest breadth change sub-portfolios across market cap quintiles during month $t + n$ before stocks are re-sorted into (possibly) new portfolios The results are expressed as monthly excess returns in percentages. Standard errors are in parentheses.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
Month $t + 2$	-0.96**	-0.94**	-0.02	-0.18	-0.67**	0.20
	(0.21)	(0.21)	(0.24)	(0.18)	(0.17)	(0.26)
Month $t + 3$	-0.85**	-0.90**	-0.02	-0.18	-0.61**	0.30
	(0.21)	(0.22)	(0.23)	(0.16)	(0.19)	(0.25)
Month $t + 4$	-0.76**	-0.76**	-0.27	-0.16	-0.45**	0.15
	(0.19)	(0.19)	(0.32)	(0.18)	(0.17)	(0.23)
Month $t + 5$	-0.35*	-0.38*	0.37	-0.23	-0.28	-0.12
	(0.16)	(0.17)	(0.28)	(0.16)	(0.15)	(0.21)
Month $t + 6$	-0.17	-0.14	0.11	0.08	-0.10	0.14
	(0.20)	(0.20)	(0.24)	(0.16)	(0.16)	(0.26)
Month $t + 7$	-0.14	-0.12	-0.23	0.24	-0.02	0.27
	(0.20)	(0.20)	(0.26)	(0.17)	(0.19)	(0.22)
Month $t + 8$	-0.06	-0.07	0.01	-0.21	-0.21	0.22
	(0.17)	(0.18)	(0.24)	(0.15)	(0.13)	(0.22)
Month $t + 9$	0.19	0.13	0.31	-0.04	-0.14	0.23
	(0.20)	(0.21)	(0.22)	(0.17)	(0.17)	(0.21)
Month $t + 10$	-0.13	-0.16	-0.17	-0.09	-0.27	-0.07
	(0.19)	(0.18)	(0.27)	(0.17)	(0.15)	(0.24)
Month $t + 11$	-0.11	-0.12	0.00	0.18	0.02	0.29
	(0.19)	(0.20)	(0.24)	(0.17)	(0.16)	(0.20)
Month $t + 12$	-0.17	-0.21	-0.12	0.07	0.06	0.19
	(0.16)	(0.15)	(0.24)	(0.15)	(0.17)	(0.24)

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

Table 4. Breadth change portfolio four-factor monthly alphas among subsamples

This table shows the 4-factor alphas from zero-investment portfolios that are formed based on breadth change within a subset of our sample: between 1996 and 2001; between 2002 and 2007; within only the smallest market cap quintile; within only the largest market cap quintile; or excluding stocks for which less than one year has elapsed since their IPO. Breadth change is either equal- or wealth-weighted among all, retail, or institutional investors. We sort stocks into market cap quintiles based on their month $t-1$ tradable market cap, and calculate $t-1$ breadth change quintile breakpoints (for all and retail investors) or 10th and 90th percentile $t-1$ breadth change breakpoints (for institutional investors). We value-weight stocks within each market cap × breadth change sub-portfolio. With the exception of the portfolios that include only the smallest or largest market cap quintile, the portfolios whose returns we report are long an equal-weighted portfolio of all the highest breadth change sub-portfolios across the market cap quintiles and short an equal-weighted portfolio of all the lowest breadth change sub-portfolios across market cap quintiles. Stocks are held for one month 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	-2.22**	-2.23**	-0.79	-1.10**	-1.94**	0.53
	(0.31)	(0.31)	(0.55)	(0.29)	(0.27)	(0.43)
2002-2007	-1.42**	-1.39**	0.29	0.32	-0.73**	0.99**
	(0.31)	(0.31)	(0.23)	(0.19)	(0.20)	(0.27)
Smallest market cap quintile	-1.61**	-1.58**	0.60	-0.52	-0.73*	0.32
	(0.33)	(0.36)	(0.56)	(0.36)	(0.33)	(0.54)
Largest market cap quintile	-1.86**	-1.84**	-0.13	0.19	-1.40**	1.69**
	(0.45)	(0.45)	(0.56)	(0.39)	(0.35)	(0.59)
No stocks < 1 year old	-1.85**	-1.84**	-0.36	-0.44*	-1.38**	0.71**
	(0.21)	(0.21)	(0.31)	(0.18)	(0.17)	(0.27)

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

Table 5. Breadth change portfolio returns: Fama-MacBeth regressions

This table shows coefficients from a monthly Fama-MacBeth regression where the dependent variable is a stock's month t return. Depending on the column, breadth change from $t-2$ to $t-1$ is equal-weighted or wealth-weighted, and calculated among all, retail, or institutional investors. The variable $\lambda_{i,t-1}$ is the Merton shadow cost of incomplete information defined in equation (1), and $\Delta\log(IO_{i,t-1})$ is the change between month $t-2$ and $t-1$ in the log of the fraction of the stock's shares held by institutions. Tradable market cap is as of the end of month $t-1$. Book-to-market is the ratio as of the most recent end of June. Prior year return covers the period from $t-12$ to $t-1$. Prior quarter turnover is the average monthly turnover from $t-3$ to $t-1$ and is expressed as a percentage. Average R^2 is the time-series average of the cross-sectional regressions' R^2 values. Standard errors are in parentheses.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
$\Delta\text{Breadth}_{i,t-1}$	-12.247**	-12.277**	0.548	-0.534	-4.388**	0.054
	(3.200)	(3.201)	(0.434)	(0.358)	(1.111)	(0.047)
$\lambda_{i,t-1}$	52.966**	52.964**	59.804**	90.386**	90.186**	96.980**
	(11.540)	(11.540)	(12.907)	(16.597)	(16.557)	(16.723)
$\Delta\log(IO_{i,t-1})$	0.004	0.003	0.024	-0.002	-0.016	0.006
	(0.118)	(0.118)	(0.138)	(0.127)	(0.127)	(0.131)
log(Tradeable	-0.630**	-0.630**	-0.714**	-0.678**	-0.721**	-0.720**
market cap)	(0.224)	(0.224)	(0.218)	(0.228)	(0.228)	(0.221)
Book-to-	0.853	0.853	0.946	1.118	1.052	1.104
market	(0.605)	(0.605)	(0.585)	(0.584)	(0.585)	(0.586)
Prior year	0.503	0.503	0.524	0.432	0.437	0.521
return / 100	(0.726)	(0.726)	(0.697)	(0.705)	(0.703)	(0.726)
Prior quarter	-0.872**	-0.872**	-0.897**	-0.868**	-0.895**	-1.013**
turnover	(0.231)	(0.231)	(0.229)	(0.230)	(0.223)	(0.220)
Constant	10.999**	10.999**	12.064**	11.528**	12.077**	12.069**
	(3.143)	(3.143)	(3.093)	(3.184)	(3.177)	(3.135)
# months	135	135	135	135	135	135
Average R^2	0.139	0.139	0.136	0.136	0.138	0.136

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

Table 6. Cross-sectional predictors 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* among all, retail, or institutional investors. The variable $\Delta\log(IO_{i,t-1})$ is the change between month $t-2$ and $t-1$ in the log of the fraction of the stock's shares held by institutions. Tradable market cap is as of the end of month $t-1$. Book-to-market is the ratio as of the most recent end of June. Prior year return covers the period from $t-12$ to $t-1$. Prior quarter turnover is the average monthly turnover from $t-3$ to $t-1$ and is expressed as a percentage. Average R^2 is the time-series average of the cross-sectional regressions' R^2 values. Standard errors are in parentheses.

	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Inst.	Total	Retail	Inst.
$\Delta\log(IO_{i,t-1})$	-0.001**	-0.001**	-0.005*	0.006**	0.001	-0.018
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.022)
log(Tradeable market cap)	0.002	0.002	-0.013**	-0.033**	-0.021**	-0.148**
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.045)
Book-to-market	-0.020**	-0.020**	-0.014	-0.023	-0.029**	0.044
	(0.005)	(0.005)	(0.008)	(0.012)	(0.007)	(0.123)
Prior year return / 100	0.008*	0.008*	0.022**	0.043**	0.012**	0.218**
	(0.003)	(0.003)	(0.007)	(0.008)	(0.004)	(0.063)
Prior quarter turnover	0.007**	0.007**	-0.005	0.000	0.000	-0.036
	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.028)
Years since IPO	-0.001	-0.001	0.001	0.000	-0.001	0.007
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.009)
Constant	-0.040	-0.040	0.159**	0.412**	0.252**	1.860**
	(0.024)	(0.024)	(0.056)	(0.068)	(0.050)	(0.592)
# months	135	135	135	135	135	135
Average R^2	0.074	0.074	0.035	0.045	0.055	0.040

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

Table 7. Breadth change time series summary statistics

The aggregate daily or monthly breadth change is the average breadth change for all SSE stocks over the past day or past month, weighted by each stock's tradable market cap at $t-1$. 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.

Panel A: Monthly breadth changes						
	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Institutional	Total	Retail	Institutional
Mean	0.009	0.009	-0.026	-0.075	-0.045	-0.296
Std. dev.	0.045	0.045	0.082	0.120	0.086	0.871
Autocorrelation	0.321	0.322	0.076	0.330	0.404	-0.116
N	137	137	137	137	137	137
Panel B: Daily breadth changes						
	Equal-weighted breadth change			Wealth-weighted breadth change		
	Total	Retail	Institutional	Total	Retail	Institutional
Mean	0.001	0.001	-0.001	0.004	0.005	0.000
Std. dev.	0.005	0.005	0.015	0.026	0.016	0.250
Autocorrelation	0.439	0.432	-0.012	0.132	0.244	0.070
N	2,643	2,643	2,643	2,643	2,643	2,643

Table 8. Relationship between monthly market returns and aggregate monthly breadth changes

Dependent variables are indicated in the column headings. R_t is month t's aggregate Chinese stock market return in excess of the riskfree return. Depending on the column and panel, the variable $\Delta Breadth_t$ denotes equal-weighted or wealth-weighted breadth change among all, retail, or institutional investors. The variable $\Delta\log(IO_t)$ is the change from month-end t – 1 to month-end t in the log fraction of the SSE tradable market cap owned by institutions. Newey-West standard errors with one lag are in parentheses.

Panel A: Total breadth change								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	R_t		$\Delta Breadth_t$		R_t		$\Delta Breadth_t$	
R_t			0.001				-0.004**	
			(0.001)				(0.001)	
$\Delta\log(IO_t)$			-0.213**				0.169	
			(0.075)				(0.125)	
$\Delta Breadth_{t-1}$	-26.857	-26.482		0.357	-23.449**	-23.219**		0.257**
	(18.347)	(23.816)		(0.205)	(6.735)	(5.943)		(0.096)
R_{t-1}		0.178		0.001		0.066		-0.004**
		(0.100)		(0.001)		(0.087)		(0.001)
$\Delta\log(IO_{t-1})$		1.543		0.037		11.086		-0.127
		(14.885)		(0.034)		(10.973)		(0.120)
Constant	2.295**	1.935**	0.007*	0.004	0.303	0.203	-0.066**	-0.049**
	(0.851)	(0.736)	(0.003)	(0.003)	(0.832)	(0.795)	(0.011)	(0.010)
N	136	135	136	135	136	135	136	135
Panel B: Retail breadth change								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	R_t		$\Delta Breadth_t$		R_t		$\Delta Breadth_t$	
R_t			0.001				-0.002	
			(0.001)				(0.001)	
$\Delta\log(IO_t)$			-0.212**				-0.146	
			(0.075)				(0.088)	
$\Delta Breadth_{t-1}$	-26.748	-26.326		0.359	-26.999**	-23.526*		0.402**
	(18.388)	(23.880)		(0.206)	(9.343)	(9.279)		(0.130)
R_{t-1}		0.178		0.001		0.125		-0.002*
		(0.100)		(0.001)		(0.093)		(0.001)
$\Delta\log(IO_{t-1})$		1.595		0.037		3.775		0.135
		(14.884)		(0.033)		(12.167)		(0.098)
Constant	2.293**	1.933**	0.007*	0.004	0.862	0.768	-0.042**	-0.023**
	(0.851)	(0.736)	(0.003)	(0.003)	(0.832)	(0.828)	(0.009)	(0.005)
N	136	135	136	135	136	135	136	135

Panel C: Institutional breadth change								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	R_t		$\Delta Breadth_t$		R_t		$\Delta Breadth_t$	
R_t			-0.003*				-0.030**	
			(0.001)				(0.011)	
$\Delta log(IO_t)$			0.228**				5.332**	
			(0.064)				(0.883)	
$\Delta Breadth_{t-1}$	-18.424*	-19.069		0.086	-0.375	-1.064		-0.049
	(8.771)	(12.552)		(0.112)	(0.800)	(1.231)		(0.133)
R_{t-1}		0.102		-0.001		0.132		-0.025*
		(0.112)		(0.001)		(0.097)		(0.011)
$\Delta log(IO_{t-1})$		11.518		-0.088		12.844		-1.663
		(12.377)		(0.074)		(14.299)		(1.701)
Constant	1.586	1.379	-0.019**	-0.023**	1.948*	1.500	-0.226**	-0.273**
	(0.882)	(0.813)	(0.005)	(0.007)	(0.877)	(0.765)	(0.048)	(0.072)
N	136	135	136	135	136	135	136	135

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

Table 9. Relationship between daily market returns and aggregate total daily breadth changes

Dependent variables are indicated in the column headings. R_t is day t's aggregate Chinese stock market return in excess of the riskfree return. Depending on the column, the variable ΔBreadth denotes equal-weighted or wealth-weighted breadth change among all investors in Panel A, among retail investors in Panel B, and among institutional investors in Panel C. The variable $\Delta\log(IO_t)$ is the change from day t – 1 to day t in the log fraction of the SSE tradable market cap owned by institutions. Newey-West standard errors with five lags are in parentheses.

	Panel A: Total breadth change							
	Equal-weighted breadth change				Wealth-weighted breadth change			
	R_t		$\Delta Breadth_t$		R_t		$\Delta Breadth_t$	
R_t			-0.001**				-0.001	
			(0.000)				(0.001)	
$\Delta\log(IO_t)$			-0.096**				0.323*	
			(0.022)				(0.150)	
$\Delta Breadth_{t-1}$	-16.482	-9.925		0.428**	1.582	0.344		0.093*
	(8.423)	(9.770)		(0.063)	(1.674)	(1.808)		(0.044)
$\Delta Breadth_{t-2}$	-2.471	-3.287		0.005	-0.678	-1.036		0.096**
	(10.638)	(12.401)		(0.061)	(2.087)	(2.189)		(0.029)
$\Delta Breadth_{t-3}$	1.105	8.298		0.095	2.124	2.115		0.143**
	(11.701)	(13.719)		(0.056)	(2.033)	(2.040)		(0.035)
$\Delta Breadth_{t-4}$	-8.895	-3.074		0.030	-1.010	-1.419		0.077
	(10.724)	(12.692)		(0.053)	(1.329)	(1.435)		(0.040)
$\Delta Breadth_{t-5}$	-1.572	0.614		0.029	-0.137	0.059		-0.118
	(9.117)	(10.377)		(0.059)	(1.909)	(1.958)		(0.131)
R_{t-1}		-0.034		0.001**		-0.024		0.000
		(0.029)		(0.000)		(0.028)		(0.001)
R_{t-2}		0.002		0.000		0.001		0.001*
		(0.029)		(0.000)		(0.027)		(0.000)
R_{t-3}		0.048		0.000**		0.039		0.000
		(0.031)		(0.000)		(0.027)		(0.000)
R_{t-4}		0.025		0.000*		0.025		0.002**
		(0.027)		(0.000)		(0.024)		(0.000)
R_{t-5}		0.017		0.000		0.012		0.000
		(0.027)		(0.000)		(0.025)		(0.000)
$\Delta\log(IO_{t-1})$		9.680**		-0.024		10.396**		-0.001
		(3.124)		(0.014)		(3.114)		(0.044)
$\Delta\log(IO_{t-2})$		1.650		-0.014		2.494		-0.043
		(3.005)		(0.013)		(3.242)		(0.034)
$\Delta\log(IO_{t-3})$		2.055		-0.016		0.994		-0.176**
		(2.697)		(0.011)		(2.674)		(0.063)
$\Delta\log(IO_{t-4})$		4.365		0.000		5.323*		-0.102
		(2.535)		(0.009)		(2.631)		(0.057)
$\Delta\log(IO_{t-5})$		0.925		0.002		0.885		0.064
		(2.390)		(0.009)		(2.536)		(0.035)
Constant	0.099**	0.076*	0.001**	0.000**	0.068*	0.070*	0.004**	0.003**
	(0.032)	(0.031)	(0.000)	(0.000)	(0.032)	(0.031)	(0.001)	(0.001)
N	2638	2638	2643	2638	2638	2638	2643	2638

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

Panel B: Retail breadth change								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	R_t		$\Delta Breadth_t$		R_t		$\Delta Breadth_t$	
R_t			-0.001**				-0.001	
			(0.000)				(0.000)	
$\Delta log(IO_t)$			-0.095**				-0.128**	
			(0.022)				(0.045)	
$\Delta Breadth_{t-1}$	-16.532	-9.951		0.426**	2.612	3.958		0.068
	(8.466)	(9.820)		(0.063)	(3.180)	(3.046)		(0.088)
$\Delta Breadth_{t-2}$	-2.388	-3.186		0.007	-5.616	-5.205		0.068
	(10.655)	(12.407)		(0.061)	(4.046)	(3.972)		(0.047)
$\Delta Breadth_{t-3}$	1.096	8.293		0.095	9.380**	10.544**		0.186**
	(11.791)	(13.817)		(0.056)	(3.285)	(3.181)		(0.070)
$\Delta Breadth_{t-4}$	-8.758	-2.811		0.029	-2.160	-1.038		0.169*
	(10.781)	(12.755)		(0.053)	(2.658)	(2.779)		(0.085)
$\Delta Breadth_{t-5}$	-1.609	0.577		0.031	-0.288	0.170		0.131
	(9.162)	(10.429)		(0.058)	(3.245)	(3.168)		(0.071)
R_{t-1}		-0.034		0.001**		-0.018		0.000
		(0.029)		(0.000)		(0.029)		(0.000)
R_{t-2}		0.002		0.000		-0.007		0.001**
		(0.029)		(0.000)		(0.027)		(0.000)
R_{t-3}		0.048		0.000**		0.041		0.001
		(0.031)		(0.000)		(0.027)		(0.000)
R_{t-4}		0.025		0.000*		0.025		0.001**
		(0.027)		(0.000)		(0.024)		(0.000)
R_{t-5}		0.017		0.000		0.001		0.000
		(0.027)		(0.000)		(0.025)		(0.000)
$\Delta log(IO_{t-1})$		9.689**		-0.024		11.041**		-0.039
		(3.124)		(0.014)		(3.052)		(0.025)
$\Delta log(IO_{t-2})$		1.661		-0.014		2.025		-0.021
		(3.006)		(0.013)		(2.813)		(0.022)
$\Delta log(IO_{t-3})$		2.062		-0.016		2.769		-0.095
		(2.698)		(0.011)		(2.532)		(0.057)
$\Delta log(IO_{t-4})$		4.389		0.000		5.379*		-0.031
		(2.537)		(0.009)		(2.486)		(0.041)
$\Delta log(IO_{t-5})$		0.936		0.002		1.240		0.082**
		(2.389)		(0.009)		(2.311)		(0.030)
Constant	0.098**	0.076*	0.001**	0.000**	0.057	0.032	0.005**	0.001**
	(0.032)	(0.031)	(0.000)	(0.000)	(0.034)	(0.032)	(0.000)	(0.000)
N	2638	2638	2643	2638	2638	2638	2643	2638

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

Panel C: Institutional breadth change								
	Equal-weighted breadth change				Wealth-weighted breadth change			
	R_t		$\Delta Breadth_t$		R_t		$\Delta Breadth_t$	
R_t			0.001**				-0.006	
			(0.000)				(0.005)	
$\Delta\log(IO_t)$			0.302**				6.466**	
			(0.042)				(1.581)	
$\Delta Breadth_{t-1}$	8.694*	6.217		-0.009	0.115	-0.236		0.041
	(3.417)	(3.447)		(0.049)	(0.164)	(0.135)		(0.031)
$\Delta Breadth_{t-2}$	1.318	0.707		-0.044	0.226*	0.123		0.019
	(2.707)	(2.588)		(0.043)	(0.098)	(0.148)		(0.028)
$\Delta Breadth_{t-3}$	1.930	0.507		0.032	-0.127	-0.275		0.016
	(2.924)	(3.130)		(0.032)	(0.111)	(0.157)		(0.013)
$\Delta Breadth_{t-4}$	3.139	0.040		0.029	0.192	0.035		0.020
	(2.543)	(2.643)		(0.044)	(0.098)	(0.090)		(0.014)
$\Delta Breadth_{t-5}$	2.012	0.839		0.037	0.228*	0.201		-0.374
	(2.410)	(2.711)		(0.049)	(0.111)	(0.127)		(0.220)
R_{t-1}		-0.032		-0.001**		-0.025		-0.004
		(0.027)		(0.000)		(0.027)		(0.003)
R_{t-2}		0.005		0.000		0.002		-0.004
		(0.028)		(0.000)		(0.027)		(0.004)
R_{t-3}		0.040		0.000		0.036		0.001
		(0.027)		(0.000)		(0.027)		(0.004)
R_{t-4}		0.027		0.000		0.028		0.004
		(0.025)		(0.000)		(0.024)		(0.002)
R_{t-5}		0.014		-0.000*		0.015		-0.005
		(0.026)		(0.000)		(0.025)		(0.003)
$\Delta\log(IO_{t-1})$		8.689**		0.032		12.148**		0.976**
		(2.901)		(0.031)		(3.198)		(0.376)
$\Delta\log(IO_{t-2})$		2.165		0.015		1.383		0.348
		(3.022)		(0.026)		(3.535)		(0.331)
$\Delta\log(IO_{t-3})$		1.785		-0.014		3.608		-0.095
		(2.771)		(0.031)		(2.875)		(0.330)
$\Delta\log(IO_{t-4})$		4.884		-0.013		4.269		-0.410
		(2.637)		(0.021)		(2.739)		(0.300)
$\Delta\log(IO_{t-5})$		0.809		0.016		-0.221		1.898
		(2.559)		(0.032)		(2.632)		(0.986)
Constant	0.087**	0.076*	-0.001**	-0.001	0.075*	0.070*	0.001	0.001
	(0.033)	(0.032)	(0.000)	(0.000)	(0.034)	(0.032)	(0.004)	(0.005)
N	2638	2638	2643	2638	2638	2638	2643	2638

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

Table 10. Relationship between market return skewness and aggregate monthly breadth changes

Dependent variable is the skewness of the aggregate Chinese stock market daily returns during month *t*. Depending on the column and panel, the variable $\Delta\text{Breadth}_t$ denotes equal-weighted or wealth-weighted breadth change among all, retail, or institutional investors. The variable $\Delta\log(IO_t)$ is the change from month-end $t-1$ to month-end t in the log fraction of the SSE tradable market cap owned by institutions. Newey-West standard errors with one lag are in parentheses.

	Equal-weighted		Wealth-weighted	
Panel A: Total breadth change				
$\Delta\text{Breadth}_{t-1}$	-2.254	-2.559	1.362**	0.742
	(1.399)	(1.640)	(0.508)	(0.567)
R_{t-1}		-0.030**		-0.028**
		(0.007)		(0.008)
$\Delta\log(IO_{t-1})$		-0.469		-0.050
		(0.523)		(0.401)
Constant	-0.070	-0.009	0.012	0.022
	(0.083)	(0.082)	(0.100)	(0.097)
N	136	135	136	135
Panel B: Retail breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\text{Breadth}_{t-1}$	-2.275	-2.583	1.089	0.508
	(1.402)	(1.640)	(0.670)	(0.914)
R_{t-1}		-0.030**		-0.031**
		(0.007)		(0.008)
$\Delta\log(IO_{t-1})$		-0.473		0.149
		(0.522)		(0.395)
Constant	-0.070	-0.009	-0.042	-0.006
	(0.083)	(0.082)	(0.098)	(0.095)
N	136	135	136	135
Panel B: Institutional breadth change				
	Equal-weighted		Wealth-weighted	
$\Delta\text{Breadth}_{t-1}$	0.715	-0.547	0.043	-0.078
	(0.603)	(0.747)	(0.061)	(0.101)
R_{t-1}		-0.033**		-0.034**
		(0.009)		(0.008)
$\Delta\log(IO_{t-1})$		0.200		0.491
		(0.436)		(0.656)
Constant	-0.072	-0.038	-0.077	-0.045
	(0.090)	(0.084)	(0.090)	(0.090)
N	136	135	136	135

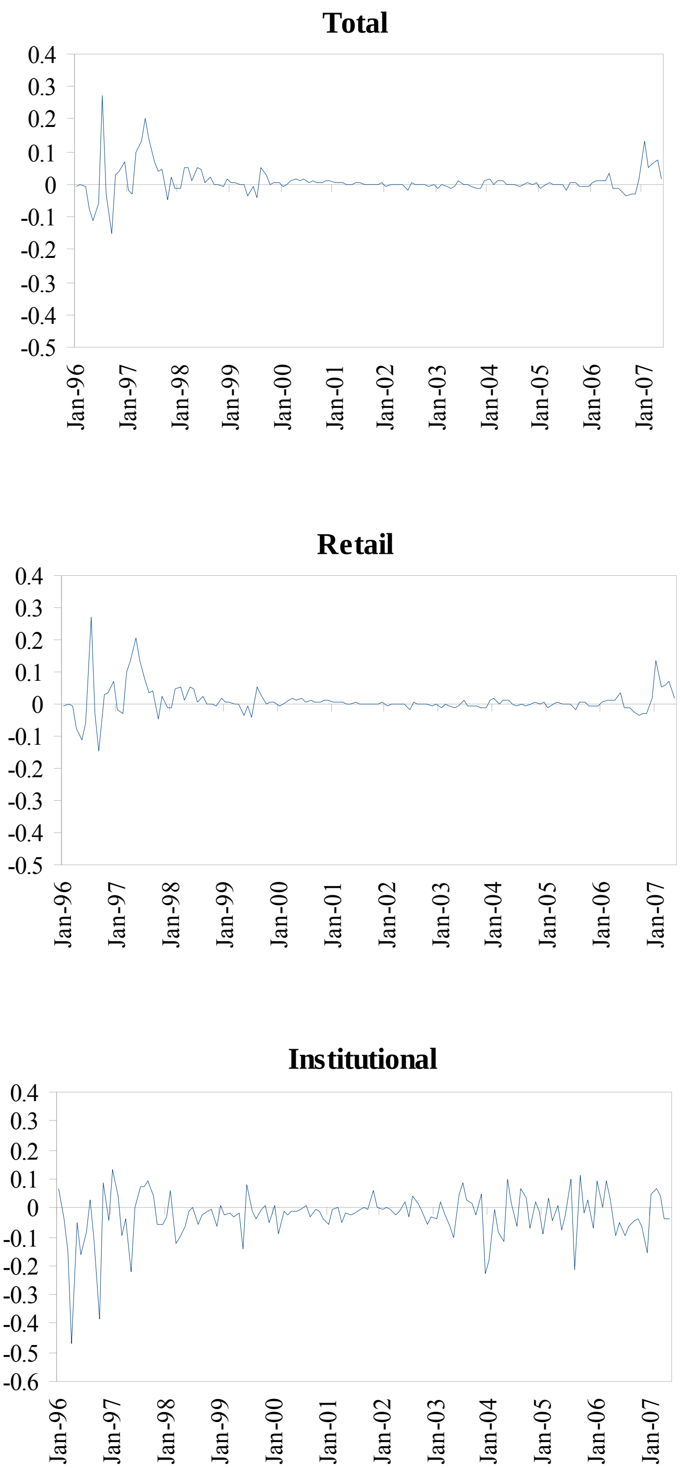

Figure 1. Aggregate equally-weighted breadth change monthly time series

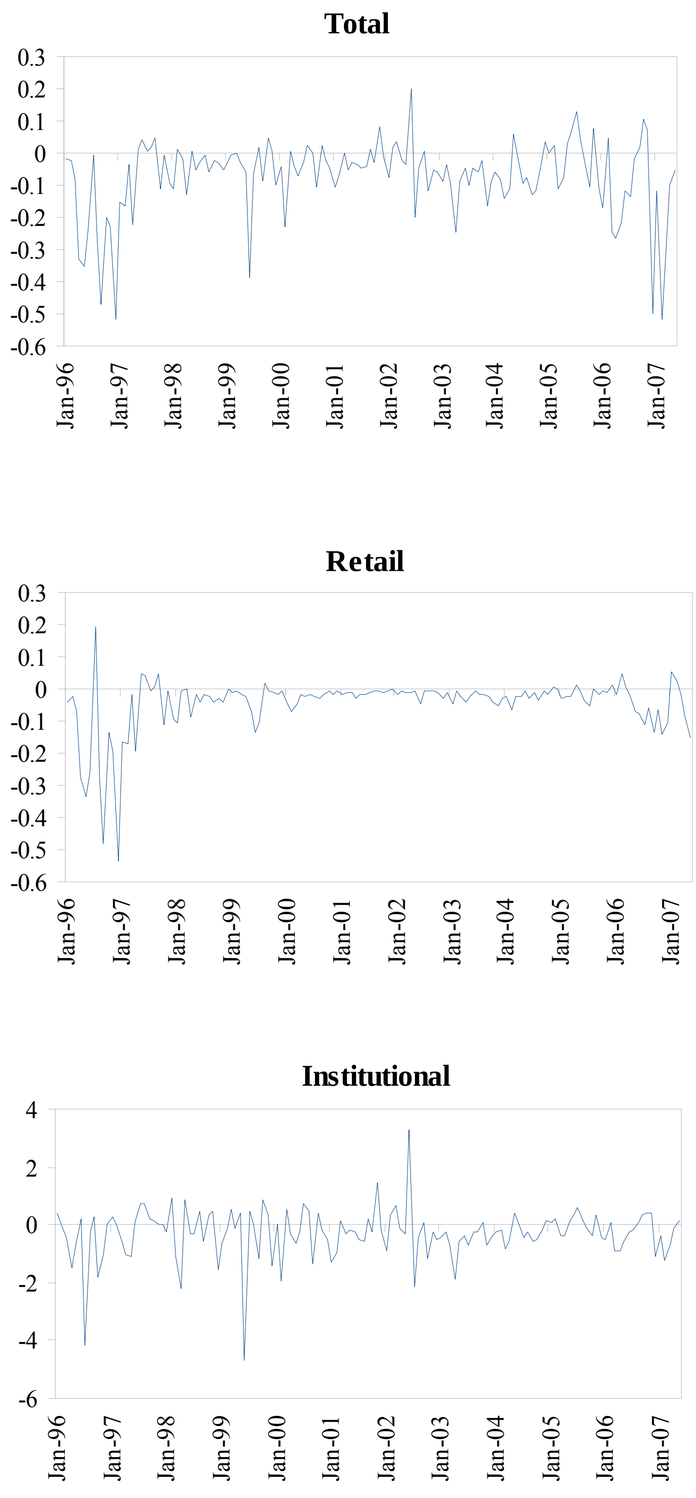

Figure 2. Aggregate wealth-weighted breadth change monthly time series