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Investor Sentiment, Disagreement, and the Breadth–Return Relationship

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We study the cross-sectional breadth–return relation by assuming that investors subject to market sentiment hold a biased belief in the aggregate. With a dynamic multiasset model, we predict that the breadth–return relationship can be either positive or negative depending on the relative strength of two offsetting forces—disagreement and sentiment. We find evidence consistent with our predictions. The breadth–return relationship is positive when the sentiment effect is small. However, the relationship becomes negative when (i) the time-series variation of market-wide sentiment is high and (ii) the cross-sectional dispersion of firm-specific exposure to market-wide sentiment variation is large. Our unified framework reconciles a few seemingly inconsistent empirical studies in this literature and explains puzzling cross-sectional return patterns observed during the Internet bubble and the subprime crisis periods.

Key words: investor sentiment; disagreement; breadth of ownership; cross-sectional stock returns
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1. Introduction

What can we learn about the future returns of a stock when we observe many investors buying in and out of it? Chen et al. (2002) argued that a stock's ownership breadth (i.e., the percentage of investors with long positions) positively predicts its future returns. The idea, which dates back to Miller (1977), is a combination of short-sales constraints and investor disagreement: when investors cannot sell short, negative views held by pessimistic investors are not fully registered into the stock price, and therefore the stock is overvalued. A higher percentage of investors with long positions implies weaker short-sales constraints. Because weaker short-sales constraints lead to a lower degree of stock overvaluation, greater ownership breadth predicts higher future returns.

However, many behavioral studies, such as DeLong et al. (1990) and Barber et al. (2009), suggest that trading activities and asset prices can also be affected by investor sentiment—a correlated and contagious bias in investors' valuation. When investor sentiment plays a major role in the financial market, overoptimistic investors rush into a stock in a mania that leads to a high breadth of ownership, or overpessimistic investors sell a stock in a panic that leads to a low breadth of ownership. Under such circumstances, one may conjecture that a stock with a high (low) level of ownership breadth is likely to be overvalued (undervalued), and therefore it will experience a low (high) subsequent return. For example, during the Internet bubble, the number of mutual funds that held stocks of Amazon.com increased by 258% in 1999, and its price plummeted by 79.6% in 2000 as the bubble burst. In the recent subprime crisis, American International Group, Inc. (AIG) lost 78% of its mutual fund shareholders in 2009, and its stock price bounced back by 92% in 2010 as the market gradually recovered. In contrast to the findings in Chen et al. (2002), these observations seem to suggest that ownership breadth negatively predicts future returns in periods such as the Internet bubble and subprime crisis when the market is dominated by investor sentiment.

To reconcile this contrast, we incorporate both factors—disagreement and sentiment—into a dynamic multiasset version of the Chen et al. (2002) model to formalize their joint effects on the cross-sectional breadth–return relationship.[1] Our model shows that

[1] The "breadth–return relationship" in this paper refers to the relationship between the *change* in ownership breadth and the future stock returns in the cross section. As argued by Chen et al. (2002, p. 181), the level of ownership breadth "is effectively a permanent firm characteristic, with a quarterly autocorrelation of 0.99." Therefore, following their study, we also purge this firm fixed effect by focusing on the change in ownership breadth in our theoretical model and empirical tests.

the sign of the breadth–return relationship depends on which effect dominates. In the extreme case in which there is no firm-level variation in sentiment, the disagreement effect dominates, and greater ownership breadth proxies for less-binding short-sales constraints and predicts higher future returns. Therefore, consistent with Chen et al. (2002), the cross-sectional breadth–return relation is positive. In the other extreme case, in which there is no firm-level variation in disagreement, the sentiment effect overwhelms the disagreement effect, and greater ownership breadth represents investors being more optimistic and predicts a lower future return. As a result, the breadth–return relationship turns negative.

Our model yields insights into the decomposition of firm-level sentiment variation. Specifically, firm-level sentiment variations can be regarded as a product of two components: time-series variation of market-wide sentiment and cross-sectional dispersion of firm-specific exposures to market-wide sentiment. The first component shows that, in the time series, sentiment-driven trading can distort prices for many stocks, triggering future reversals. The second component ensures that, in the cross section, each stock is affected by market-wide sentiment in different degrees, so that the cross-sectional breadth–return pattern can be detected. To illustrate their importance in maintaining the negative cross-sectional breadth–return relationship, let us consider the Internet bubble example. If there had been no time-series waxing and waning of enthusiasm for technology companies, we would not have had the irrational purchases initiating the bubble or the later fire sales that burst the bubble; if high-tech firms and non-high-tech firms react to market-wide sentiment in the same way, we could not detect any difference of sentiment-driven changes of ownership breadth in the cross section so that testing the (cross-sectional) breadth–return relationship is impossible.

The two components affecting the sentiment effect yield two empirical predictions: the cross-sectional breadth–return relationship tends to be negative (i) when the market-wide sentiment is volatile over time and/or (ii) when firm-level exposures to market sentiment are dispersed at the cross section. We find supporting evidence for these predictions using mutual fund holdings data and a market-wide sentiment index developed by Baker and Wurgler (2006, 2007). First, in the quarters when the Baker–Wurgler sentiment index exhibits significant time-series variations, breadth *negatively* predicts future returns; for remaining quarters with low variations in the index, the breadth–return relationship remains significantly positive. Second, we capture the cross-sectional dispersion of firm-specific exposure to the market-level sentiment variations by the sentiment beta defined in Baker and Wurgler (2007). We show that, in the cross section, the breadth–return relationship is more negative among firms with a larger dispersion in sentiment beta, when the time-series variation of market-wide sentiment index is high.

Our paper contributes to the literature in two ways. Theoretically, our model shows the importance of incorporating behavioral biases into a standard rational asset-pricing theory. With a realistic assumption that investors sometimes have biased beliefs in the aggregate, our dynamic model shows that the relationship between breadth and future returns can be positive or negative, conditional on whether the variations in disagreement or in sentiment are the main driving force of the trading activities. Empirically, our study helps to reconcile the apparently conflicting findings in previous studies. In the U.S. market before 1998, Chen et al. (2002) found a positive breadth–return correlation. However, such a pattern disappeared when Nagel (2005) incorporated the Internet bubble-burst period into the study. We suggest that the sentiment variations around the Internet bubble-burst period in Nagel's sample were high enough to negate the positive breadth–return relationship driven by disagreement. Similarly, the negative breadth–return relationship for Chinese stocks documented by Choi et al. (2012) may be explained by a significant impact of individual investors on stock prices and a persistent domination of investor sentiment in the Chinese stock market.

2. The Model

2.1. Setup

Consider a dynamic economy with one consumption good. Time is discrete and infinite: $t = 0, 1, 2, \ldots$. There are $N + 1$ tradable assets: one bond, which is in perfectly elastic supply at a constant gross interest rate $R_f > 1$, and N stocks, each of which is in limited supply (normalized as 1). Each share of stock j pays a dividend $\tilde{D}_t^j$ at date t. The dividend $\tilde{D}_t^j$ is governed by the process:

$$\tilde{D}_t^j = F + \tilde{\varepsilon}_t^j. \tag{1}$$

Here, $F > 0$ is the unconditional mean of $\tilde{D}_t^j$ and represents the "fundamental" of the stock, and $\tilde{\varepsilon}_t^j \sim N(0, 1)$ is the shock to $\tilde{D}_t^j$, which is assumed to be independent over time and across stocks.[2] Let $\tilde{P}_t^j$ be the (ex-dividend) share price of stock j at date t.

There are two classes of traders. The first class is a continuum $[0, 1]$ of arbitrageurs. They may go

[2] We assume that cash flows are independent across stocks to isolate the impact of disagreement and sentiment, which complements the recent studies focusing on the implications of cash flow correlations in multiasset settings (e.g., Andrade et al. 2008, Veldkamp and Wolfers 2007).

long or short in each asset, and they have correct beliefs about the dividend processes. Arbitrageurs can be thought of as hedge funds that face no restrictions on shorting. At each date t, arbitrageurs choose consumption $\tilde{C}_{A,t}$ and portfolio $(\tilde{Z}^1_{A,t}, \ldots, \tilde{Z}^N_{A,t}) \in \mathbf{R}^N$ to maximize expected utility $E_t[-\sum_{s=0}^{\infty} \delta_A^s e^{-\tau_A^{-1}\tilde{C}_{A,t+s}}]$, subject to the standard budget constraint, $\tilde{W}_{A,t+1} = R_f(\tilde{W}_{A,t} - \tilde{C}_{A,t}) + \sum_{j=1}^{N} \tilde{Z}^j_{A,t}(\tilde{P}^j_{t+1} + \tilde{D}^j_{t+1} - R_f\tilde{P}^j_t)$, where $E_t[\cdot]$ is the expectation operator conditional on the information up to date t, $\delta_A \in (0,1)$ is the time discount factor, $\tau_A > 0$ is the risk-tolerance parameter, and $\tilde{W}_{A,t}$ is the preconsumption wealth at date t.

The second class of traders is a continuum $[0,1]$ of buyers who can only take long positions in stocks. One might interpret the buyers as mutual funds, who are usually prohibited from shorting stocks. Buyers do not realize that dividends follow independent and identically distributed (i.i.d.) processes as characterized by Equation (1), but instead think that the mean of dividends is time varying and forecastable. Specifically, at date t, buyer i perceives

$$\tilde{D}^j_{t+1} = \tilde{V}^j_{i,t} + \tilde{\varepsilon}^j_{t+1}, \tag{2}$$

where $\tilde{V}^j_{i,t}$ is her forecast for the next period dividend $\tilde{D}^j_{t+1}$ of stock j, and $\tilde{\varepsilon}^j_{t+1} \sim N(0,1)$ is her forecast error, which she perceives to be independent over time and across stocks.[3]

Let $E^i_t[\cdot]$ be the conditional expectation for buyer i at time t. At each date, she maximizes her subjective expected utility $E^i_t[-\sum_{s=0}^{\infty} \delta_B^s e^{-\tau_B^{-1}\tilde{C}_{Bi,t+s}}]$ by choosing onsumption $\tilde{C}_{Bi,t}$ and portfolios $(\tilde{Z}^1_{Bi,t}, \ldots, \tilde{Z}^N_{Bi,t}) \in \mathbf{R}^N_+$, subject to the budget constraint $\tilde{W}_{Bi,t+1} = R_f(\tilde{W}_{Bi,t} - \tilde{C}_{Bi,t}) + \sum_{j=1}^{N} \tilde{Z}^j_{Bi,t}(\tilde{P}^j_{t+1} + \tilde{D}^j_{t+1} - R_f\tilde{P}^j_t)$, where $\tilde{W}_{Bi,t}$ is her preconsumption wealth at date t, $\delta_B \in (0,1)$ is her time-discount factor, and $\tau_B > 0$ is her risk-tolerance parameter. Let $\tilde{Z}^{1*}_{Bi,t}$ be buyer i's perceived optimal holdings of stock j relative to her own belief. Then, breadth of ownership $\tilde{B}^j_t$ for stock j at date t is defined as the fraction of date t buyers who are long in stock j; that is,

$$\tilde{B}^j_t \triangleq \int_0^1 1_{\{\tilde{Z}^{1*}_{Bi,t} \geq 0\}}\, di, \tag{3}$$

where $1_{\{\cdot\}}$ is an indicator function that takes the value 1 if the condition in parentheses is satisfied and 0 otherwise.

[3] We use Equation (2) as a device of modeling buyers' subjective beliefs without specifying where these beliefs come from (see also Barberis et al. 1998). Alternatively, Equation (2) can be interpreted as a reduced form of overconfident buyers observing uninformative signals (Scheinkman and Xiong 2003).

2.2. Evolution of Buyers' Beliefs

Because variable $\tilde{V}^j_{i,t}$ determines buyers' subjective beliefs through Equation (2), its structure drives the economy's disagreement and sentiment. We assume that $\tilde{V}^j_{i,t}$ entertains the following structure:

$$\tilde{V}^j_{i,t} = F + \tilde{S}^j_t + \eta_i \tilde{H}^j_t. \tag{4}$$

That is, buyer i's forecast $\tilde{V}^j_{i,t}$ for the next-period dividend includes three elements. The first is the true mean F of future dividends. The second is $\tilde{S}^j_t \in \mathbf{R}$, which is common to all buyers and represents their *aggregate* forecast bias: When $\tilde{S}^j_t > 0$, the average forecast of buyers is greater than the true mean F of future dividends, which means that they are optimistic about stock j as a group, and when $\tilde{S}^j_t < 0$ they are pessimistic. We therefore call $\tilde{S}^j_t$ *sentiment*.

The third element determining $\tilde{V}^j_{i,t}$ is a product of two variables—a buyer-specific variable, $\eta_i \in [-1,1]$, and a stock-specific variable, $\tilde{H}^j_t > 0$. We assume that η_i is uniformly distributed across buyers, which in turn implies that $\tilde{V}^j_{i,t}$ is also uniformly distributed on the interval of $[F + \tilde{S}^j_t - \tilde{H}^j_t, F + \tilde{S}^j_t + \tilde{H}^j_t]$. Therefore, $\tilde{H}^j_t$ captures the heterogeneity of buyers' forecasts, and we label it *disagreement*: a higher $\tilde{H}^j_t$ means that buyers hold more diverse beliefs about the next-period dividends. Parameter η_i determines buyer i's degree of optimism relative to other buyers, and a higher η_i means that buyer i is more optimistic than her peers.

Equation (4) indicates that the evolution of $\tilde{V}^j_{i,t}$ is driven by the dynamics of stock-level disagreement and sentiment, $\tilde{H}^j_t$ and $\tilde{S}^j_t$. We assume that $\tilde{H}^j_t$ and $\tilde{S}^j_t$ are governed by a loading structure:

$$\tilde{H}^j_t = b^j_H \tilde{H}_t \quad \text{and} \quad \tilde{S}^j_t = b^j_S \tilde{S}_t. \tag{5}$$

Here, $\tilde{H}_t$ and $\tilde{S}_t$ can be, respectively, interpreted as market-level disagreement and sentiment. $\tilde{H}_t$ has a positive mean of $\mu_H > 0$ and a standard deviation of $\sigma_H > 0$, and $\tilde{S}_t$ has a mean of 0 and a standard deviation of $\sigma_S > 0$. We assume that $\tilde{H}_t$ and $\tilde{S}_t$ are mutually independent and that the process $\{\tilde{H}_t, \tilde{S}_t\}_{t=0}^{\infty}$ is i.i.d. over time.

Parameters $b^j_H > 0$ and $b^j_S \in \mathbf{R}$, respectively, capture the sensitivities of disagreement and sentiment associated with stock j to aggregate market-level disagreement and sentiment. Therefore, we call b^j_H and b^j_S *disagreement loading* and *sentiment loading* of stock j, respectively. We assume that loadings b^j_H and b^j_S are constant over time to reflect the fact that the stocks that are likely to be influenced by disagreement and sentiment typically have long-lasting characteristics (Baker and Wurgler 2007). At the cross section, for each stock j, we assume that b^j_H and b^j_S are generated by independent draws from two independent distributions: b_H^j is drawn from a distribution with a mean of $\mu_{bH} > 0$ and a standard deviation of $\sigma_{bH} > 0$, and b_S^j is drawn from a distribution with a mean of $\mu_{bS} \in \mathbf{R}$ and a standard deviation of $\sigma_{bS} > 0$.

2.3. Equilibrium Characterization

At each date, the aggregate state variables of the economy are $(\tilde{H}_t, \tilde{S}_t)$, and they determine all aggregate market outcomes including prices and breadths for each stock. Arbitrageurs' individual state variables are also $(\tilde{H}_t, \tilde{S}_t)$ that affect their decisions through prices.[4] The individual state variables of buyers are $(\tilde{H}_t, \tilde{S}_t, \eta_i)$, and they, through Equations (2), (4), and (5), determine the beliefs of buyers and hence their consumption and investment decisions. We adopt the following dynamic equilibrium concept of Radner (1972), known as *equilibrium of plans, prices, and price expectations*.

Definition 1. An equilibrium consists of price functions $P^1(\tilde{H}_t, \tilde{S}_t), \ldots, P^N(\tilde{H}_t, \tilde{S}_t)$, arbitrageurs' decision rules $C_A(\tilde{H}_t, \tilde{S}_t)$, $Z_A^1(\tilde{H}_t, \tilde{S}_t), \ldots, Z_A^N(\tilde{H}_t, \tilde{S}_t)$, and buyers' decision rules $C_B(\tilde{H}_t, \tilde{S}_t, \eta_i)$, $Z_B^1(\tilde{H}_t, \tilde{S}_t, \eta_i), \ldots,$ $Z_B^N(\tilde{H}_t, \tilde{S}_t, \eta_i)$, such that (i) decision rules maximize traders' subjective expected utility, given their beliefs and price functions; and (ii) all security markets clear, i.e.,

$$Z_A^j(\tilde{H}_t, \tilde{S}_t) + \int_0^1 Z_B^j(\tilde{H}_t, \tilde{S}_t, \eta_i)\, di = 1, \tag{6}$$

for $j = 1, 2, \ldots, N$ and almost every realization of $(\tilde{H}_t, \tilde{S}_t)$.

We characterize equilibrium stock prices by computing traders' perceived optimal investment policies (relative to their own beliefs) and by using the market-clearing conditions. Following Wang (1994), we can show that the arbitrageurs' and buyer i's value functions are

$$U_A(\tilde{W}_{A,t}; \tilde{H}_t, \tilde{S}_t) = -e^{-\gamma_A^{-1}\tilde{W}_{A,t} - \varphi_A(\tilde{H}_t, \tilde{S}_t)} \quad \text{with } \gamma_A = \tau_A R_f/(R_f - 1), \tag{7}$$

$$U_B(\tilde{W}_{B,t}; \tilde{H}_t, \tilde{S}_t, \eta_i) = -e^{-\gamma_B^{-1}\tilde{W}_{B,t} - \varphi_B(\tilde{H}_t, \tilde{S}_t, \eta_i)} \quad \text{with } \gamma_B = \tau_B R_f/(R_f - 1), \tag{8}$$

where functions $\varphi_A(\tilde{H}_t, \tilde{S}_t)$ and $\varphi_B(\tilde{H}_t, \tilde{S}_t, \eta_i)$ are endogenous. The constant-absolute-risk-aversion feature of traders' preferences means that their consumption and investment decisions are separable. In particular, the first-order conditions determining their perceived optimal holdings of stock j, $Z_{A,t}^{j*}$ and $Z_{Bi,t}^{j*}$, are

$$Z_{A,t}^{j*} = \gamma_A(E[\tilde{P}_{t+1}^j] + F - R_f\tilde{P}_t^j) + \gamma_A \mathrm{Cov}_t(\tilde{P}_{t+1}^j, \tilde{k}_{A,t+1}^*), \tag{9}$$

$$Z_{Bi,t}^{j*} = \max\{\gamma_B(E[\tilde{P}_{t+1}^j] + \tilde{V}_{i,t}^j - R_f\tilde{P}_t^j) + \gamma_B \mathrm{Cov}_t^i(\tilde{P}_{t+1}^j, \tilde{k}_{Bi,t+1}^*), 0\}, \tag{10}$$

where $E[\cdot]$ is the unconditional mean operator; $\mathrm{Cov}_t(\cdot,\cdot)$ and $\mathrm{Cov}_t^i(\cdot,\cdot)$ are the date t conditional covariance operators for arbitrageurs and buyer i, respectively; and

$$\tilde{k}_{A,t+1}^* \triangleq \frac{e^{-\gamma_A^{-1}\sum_{j=1}^N \tilde{Z}_{A,t}^{j*}\tilde{P}_{t+1}^j - \varphi_A(\tilde{H}_{t+1}, \tilde{S}_{t+1})}}{E_t[e^{-\gamma_A^{-1}\sum_{j=1}^N \tilde{Z}_{A,t}^{j*}\tilde{P}_{t+1}^j - \varphi_A(\tilde{H}_{t+1}, \tilde{S}_{t+1})}]} \quad \text{and}$$

$$\tilde{k}_{Bi,t+1}^* \triangleq \frac{e^{-\gamma_B^{-1}\sum_{j=1}^N \tilde{Z}_{Bi,t}^{j*}\tilde{P}_{t+1}^j - \varphi_B(\tilde{H}_{t+1}, \tilde{S}_{t+1}, \eta_i)}}{E_t^i[e^{-\gamma_B^{-1}\sum_{j=1}^N \tilde{Z}_{Bi,t}^{j*}\tilde{P}_{t+1}^j - \varphi_B(\tilde{H}_{t+1}, \tilde{S}_{t+1}, \eta_i)}]}.$$[5]

Equations (9) and (10) show that traders' perceived optimal stockholdings are composed of two components. The first component is a mean-variance portfolio reflecting the return-risk trade-off. The second component is a hedging portfolio reflecting traders' intertemporal hedging demand because expected returns on stocks change over time in our economy. To the extent that the hedging component is relatively small, we can analytically characterize the equilibrium price $\tilde{P}_t^j$ and breadth of ownership $\tilde{B}_t^j$ in terms of stock-level disagreement and sentiment, $\tilde{H}_t^j$ and $\tilde{S}_t^j$. We then linearize the price and breadth functions around the means of $\tilde{H}_t^j$ and $\tilde{S}_t^j$, which leads to the following proposition.[6]

Proposition 1. *The equilibrium price $\tilde{P}_t^j$ and breadth of ownership $\tilde{B}_t^j$ for stock j are approximately given as follows*:

$$\tilde{P}_t^j \approx Constant_P^j + \alpha_{P,H}\tilde{H}_t^j + \alpha_{P,S}\tilde{S}_t^j, \tag{11}$$

$$\tilde{B}_t^j \approx Constant_B - \alpha_{B,H}\tilde{H}_t^j + \alpha_{B,S}\tilde{S}_t^j, \tag{12}$$

where $Constant_P^j$, $Constant_B$, $\alpha_{P,H} > 0$, $\alpha_{P,S} > 0$, $\alpha_{B,H} > 0$, and $\alpha_{B,S} > 0$ are constants with values that are determined by the exogenous parameters R_f, γ_A, γ_B, and $\mu_{bH}\mu_H$.

[4] Here, we have followed Scheinkman and Xiong (2003) in assuming that traders can observe the aggregate state variables $(\tilde{H}_t\tilde{S}_t)$. This assumption, however, is not essential because even if they do not directly observe $(\tilde{H}_t\tilde{S}_t)$ they still can use the N stock prices to back out $(\tilde{H}_t\tilde{S}_t)$.

[5] The proofs for these demand functions and the subsequent propositions are provided in the online appendix to this paper (available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1743848).

[6] To be precise, the linearization is done for the periods in which some buyers optimally hold the stock while others do not (i.e., $0 < \tilde{B}_t^j < 1$), which is the most interesting case, because our goal is to use breadth variations to predict future returns. We can ensure that $0 < \tilde{B}_t^j < 1$ for most periods by carefully choosing the support of $\tilde{H}_t^j$ and $\tilde{S}_t^j$. In a robustness test reported in A3 of the online appendix, we also numerically solve the equilibrium without approximations for an economy with two stocks and binomially distributed market-level disagreement and sentiment, and we verify the validity of the propositions and the hypotheses derived under approximations.

2.4. Breadth–Return Relationship

The return on stock j between dates t and $t+1$ is defined as $\tilde{R}^j_{t+1} \triangleq \tilde{P}^j_{t+1} + \tilde{D}^j_{t+1} - \tilde{P}^j_t$, and the change in breadth is defined as $\Delta\tilde{B}^j_t \triangleq \tilde{B}^j_t - \tilde{B}^j_{t-1}$. Then Equations (11) and (12) in Proposition 1 imply that

$$\tilde{R}^j_{t+1} \approx \tilde{D}^j_{t+1} + \alpha_{P,H}(\tilde{H}^j_{t+1} - \tilde{H}^j_t) + \alpha_{P,S}(\tilde{S}^j_{t+1} - \tilde{S}^j_t), \quad (13)$$

$$\Delta\tilde{B}^j_t \approx -\alpha_{B,H}(\tilde{H}^j_t - \tilde{H}^j_{t-1}) + \alpha_{B,S}(\tilde{S}^j_t - \tilde{S}^j_{t-1}). \quad (14)$$

Equations (13) and (14) suggest that disagreement and sentiment deliver different influences on the cross-sectional relationship between changes in breadth $\Delta\tilde{B}^j_t$ and future returns $\tilde{R}^j_{t+1}$. Increasing disagreement about a stock will decrease breadth and predict a poor future return; i.e., both $\Delta\tilde{B}^j_t$ and $\tilde{R}^j_{t+1}$ decrease with $\tilde{H}^j_t$. As a result, cross-sectional variations in disagreement generate a positive cross-sectional breadth–return relationship. This mechanism is the one emphasized in Miller (1977) and Chen et al. (2002): When buyers have diverse opinions, pessimistic traders do not hold the asset, and only optimistic views are registered, leading to a small breadth, a high price, and a low future return. In contrast, increasing sentiment will increase breadth and predict a low future return; i.e., $\Delta\tilde{B}^j_t$ increases and $\tilde{R}^j_{t+1}$ decreases with $\tilde{S}^j_t$. Therefore, cross-sectional variations in sentiment result in a negative cross-sectional breadth–return relationship. This mechanism is new to the literature, although its intuition is straightforward: When buyers as a group become more optimistic about a stock, more of them will buy the stock, leading to a positive change in its breadth; at the same time, their increased demand pushes the equilibrium price up, generating a low future return.

Therefore, the cross-sectional breadth–return relationship can be positive or negative, depending on the relative strength of disagreement and sentiment effects. When the disagreement effect dominates, the sign of the breadth–return relation is expected to be positive; however, when the sentiment effect dominates, the sign is expected to be negative. To formalize this idea, we consider Fama–MacBeth regression coefficient $\hat{\beta}$ (Fama and MacBeth 1973) for a time series of length T, which is defined as follows:

$$\hat{\beta} = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t, \quad (15)$$

where $\hat{\beta}_t$ is the ordinary least squares coefficient in a cross-sectional regression of $\tilde{R}^j_{t+1}$ on $\Delta\tilde{B}^j_t$:

$$\hat{\beta}_t = \frac{\sum_{j=1}^{N}\big(\tilde{R}^j_{t+1} - (1/N)\sum_{j'}\tilde{R}^{j'}_{t+1}\big)\big(\Delta\tilde{B}^j_t - (1/N)\sum_{j'}\Delta\tilde{B}^{j'}_t\big)}{\sum_{j=1}^{N}\big(\Delta\tilde{B}^j_t - (1/N)\sum_{j'}\Delta\tilde{B}^{j'}_t\big)^2}. \quad (16)$$

We then use the expressions for $\tilde{R}^j_{t+1}$ and $\Delta\tilde{B}^j_t$ in Equations (13) and (14) and the law of large numbers to derive the following proposition.[7]

Proposition 2. *In a large economy with a long data period (i.e., both N and T are large), Fama–MacBeth regression coefficient $\hat{\beta}$ is approximately proportional to*

$$g(R_f, \gamma_A, \gamma_B, \mu_H\mu_{bH}) \times \sigma^2_H\sigma^2_{bH} - \sigma^2_S\sigma^2_{bS},$$

where the function $g(R_f, \gamma_A, \gamma_B, \mu_H\mu_{bH}) = (\alpha_{P,H}\alpha_{B,H})/(\alpha_{P,S}\alpha_{B,S}) > 0$ does not depend on disagreement or sentiment variation parameters (i.e., σ^2_H, σ^2_{bH}, σ^2_S, and σ^2_{bS}).

Proposition 2 clearly summarizes the impact of disagreement and sentiment on the cross-sectional breadth–return regression coefficient. Specifically, the term $g(R_f, \gamma_A, \gamma_B, \mu_H\mu_{bH}) \times \sigma^2_H\sigma^2_{bH}$ captures the regression coefficient due to disagreement. Both a higher variance σ^2_H of market-level disagreement and a higher dispersion σ^2_{bH} of cross-sectional disagreement loadings contribute to a more positive breadth-return regression coefficient. On the other hand, the term $\sigma^2_S\sigma^2_{bS}$ captures the regression coefficient due to sentiment. A higher variance σ^2_S of market-level sentiment and a higher dispersion σ^2_{bS} of cross-sectional sentiment loadings will lead to a more negative regression coefficient.

Proposition 2 yields two insights into how sentiment can affect (or even reverse) the positive relation between breadth and future stock returns documented in Chen et al. (2002). First, although many people may think that the sentiment level matters in determining the breadth–return relationship, our theory suggests that what really matters is the variation of sentiment. Second, our proposition specifies that the effect of sentiment variation on the predictive power of breadth for future returns comes not only from time-series variations in the aggregate market sentiment, as many people may expect, but also from the cross-sectional dispersion of exposure to the market-wide sentiment variations. Formally, according to Proposition 2, Fama–MacBeth regression coefficient $\hat{\beta}$ is negative if and only if

$$\sigma^2_{bS}\sigma^2_S > g(R_f, \gamma_A, \gamma_B, \mu_H\mu_{bH}) \times \sigma^2_H\sigma^2_{bH}. \quad (17)$$

Because $g(R_f, \gamma_A, \gamma_B, \mu_H\mu_{bH}) \times \sigma^2_H\sigma^2_{bH}$ is independent of sentiment parameters σ^2_S and σ^2_{bS}, an increase in σ^2_S and/or σ^2_{bS} will make Equation (17) more likely to be satisfied. As a consequence, the cross-sectional breadth–return relationship tends to be negative when market-level sentiment ($\tilde{S}_t$) is very volatile

[7] To get an analytical expression in Proposition 2, we have also assumed that the expectation of a quotient of two random variables is close to the quotient of their expectations; i.e., $E(\tilde{x}/\tilde{y}) \approx E(\tilde{x})/E(\tilde{y})$. This assumption can be viewed as a first-order approximation.

(i.e., when σ_S^2 is large) and/or when there is a large cross-sectional dispersion in sentiment loadings (i.e., when σ_{bS}^2 is large). This observation leads to the following two testable hypotheses.

Hypothesis 1. *Other things being equal, changes in breadth tend to negatively predict future returns when market-wide sentiment is volatile; that is, $\hat{\beta}$ tends to be negative when σ_S^2 is high.*

Hypothesis 2. *Other things being equal, changes in breadth tend to negatively predict future returns when the cross-sectional exposure to market-wide sentiment variation is dispersed; that is, $\hat{\beta}$ tends to be negative when σ_{bS}^2 is large.*

3. Data and Sample

3.1. Data

Following Chen et al. (2002), we use quarterly data on mutual fund holdings to calculate the change in breadth of ownership for each stock in each quarter. Our sample covers a period between the first quarter of 1980 and the last quarter of 2007.[8] The mutual fund data set provided by the Wharton Research Data Service starts from the first quarter of 1980 and the Baker–Wurgler sentiment index that we downloaded from Jeffrey Wurgler's website (http://people.stern.nyu.edu/jwurgler/; accessed May 28, 2010) and ends in December 2007.

We define key variables related to mutual fund holdings in a way identical to Chen et al. (2002). In each quarter t, we define breadth of ownership, denoted as $BREADTH_t$, as the ratio of the number of mutual funds that hold a long position in the stock to the total number of active mutual funds in the sample for that quarter. To compute the change of ownership breadth, $\Delta BREADTH_t$, we also follow Chen et al. (2002) by counting only those funds that are active in both quarters t and $t-1$.[9] $HOLD_t$ represents the aggregate ownership of all mutual funds. It is defined as the total number of shares held by mutual funds in quarter t divided by the total number of outstanding shares. $\Delta HOLD_t$ is the change of aggregate mutual fund holdings ($HOLD_t$) from the end of quarter $t-1$ to the end of quarter t.

We obtain data on stock returns, total number of outstanding shares, and trading volume from the Center for Research in Security Prices (CRSP), and data on book values of equities from COMPUSTAT. $LOGSIZE_t$ is the natural logarithm of market capitalization at the end of quarter t. BK/MKT_t is the book-to-market ratio as defined in Fama and French (1993). We use the value of book-to-market ratios as of the most recent fiscal year end before quarter t. $MOM12_t$ represents each firm's 12-month cumulative holding-period raw return to the end of quarter t. We sum share turnover every three months to compute a quarterly measure of turnover ($TURNOVER_t$), and, similar to Chen et al. (2002), we partition all firms into two groups, depending on whether the firms are listed on NASDAQ or not. In each quarter t, we demean the $TURNOVER_t$ of each firm by the average level of $TURNOVER_t$ of its own group. This exchange-adjusted $TURNOVER_t$ is denoted as $XTURNOVER_t$.

The macroeconomic variables used in our study are defined as follows. *T-Bill* $3M_t$ is the annualized three-month Treasury-bill yield in quarter t. *Term Spread*$_t$ is the difference between the average annualized 10-year T-bond yield and average annualized three-month T-bill yield in quarter t. *Default Spread*$_t$ is the difference between the average yield of bonds rated Baa and the average yield of bonds rated Aaa by Moodys in quarter t. *Div Yield*$_t$ is defined as the annualized difference between the CRSP value-weighted index return with distribution and the one without distribution in quarter t. *GDP Growth*$_t$ is the annualized real gross domestic product (GDP) growth rate in quarter t, based on 2005 dollar values. *Inflation*$_t$ is the annualized growth rate of the consumer price index in quarter t. All macroeconomic variables are obtained from the data sets provided on the websites of the U.S. Bureau of Economic Analysis (http://www.bea.gov/), the U.S. Federal Reserve (http://www.federalreserve.gov/econresdata/default.htm), and the U.S. Census Bureau (http://www.census.gov/).

Firms must satisfy several screening criteria to be included in our sample. First, firms must be incorporated in the United States, and they must be listed on the NYSE, the AMEX, or the NASDAQ. Second, we require that these stocks be identified by a CRSP share-type code of 10 or 11. Third, we limit our sample to common stocks with nonnegative book values. Finally, to make our results comparable to those in Chen et al. (2002), we follow their method and require that the market capitalization of stocks in our sample be larger than the 20th percentile cut off based on the NYSE breakpoints.

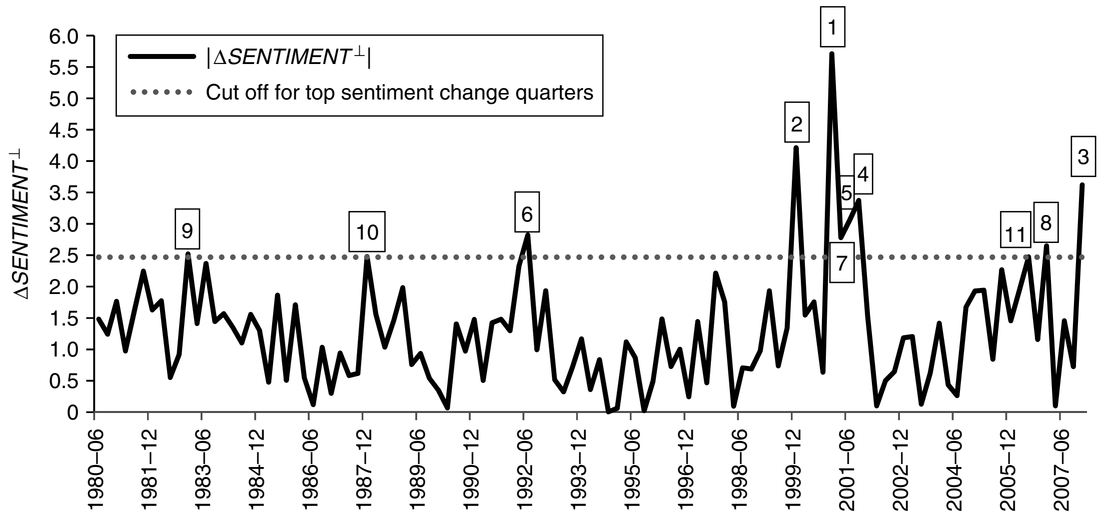
3.2. Investment Sentiment Index

Our measure of investment sentiment is the orthogonalized $\Delta SENTIMENT^{\perp}$ from Baker and Wurgler (2006, 2007). We obtain the data set that contains monthly $SENTIMENT^{\perp}$ and $\Delta SENTIMENT^{\perp}$ values, and we compute the means of $SENTIMENT^{\perp}$ (level)

[8] We have confirmed the consistency of our sample with the sample in Chen et al. (2002) for the period 1980–1998.

[9] According to this definition, funds just established or liquidated in quarter t would not be reflected in $\Delta BREADTH_t$. Specifically, we first take the number of funds that hold the stock at quarter t minus the number of funds that hold the stock at quarter $t-1$. We scale this difference by the total number of funds in the sample at quarter $t-1$ to obtain $\Delta BREADTH_t$.

Figure 1 $|\Delta SENTIMENT^{\perp}|$ **(1980–2007)**



No.	Time	$\Delta SENTIMENT$	Events
1	2000Q4	−5.71	In the middle of the burst of the Internet bubble
2	1999Q4	4.21	Internet bubble
3	2007Q4	3.62	U.S. government prepared to launch a series of bailouts to help firms in the subprime mortgage crisis
4	2001Q3	−3.37	9/11 attack
5	2001Q2	3.06	In the middle of the burst of the Internet bubble
6	1992Q2	−2.82	European exchange rate mechanism crisis
7	2001Q1	−2.78	In the middle of the burst of the Internet bubble
8	2006Q4	2.65	Peak of subprime securitization
9	1982Q4	2.52	End of 16-month recessions and recovery from Latin American debt crisis
10	1987Q4	−2.48	Black Monday crash
11	2006Q2	2.47	Toward the peak of subprime securitization

Notes. This figure provides a time-series plot of $|\Delta SENTIMENT^{\perp}|$ from the first quarter of 1980 to the last quarter of 2007. In the table below the figure, we provide a brief description of events occurring in top sentiment variation quarters.

and sums of $\Delta SENTIMENT^{\perp}$ (change) within each quarter to obtain the corresponding quarterly indices. We proxy the *time-series* variation of market-wide sentiment, σ_S^2 in Equation (17), by the absolute value of the quarterly change of sentiment, $|\Delta SENTIMENT^{\perp}|$. It is important to point out that, by its construction, our measure captures the market-wide sentiment variation *of* each quarter instead of the variation *within* each quarter.[10]

We plot its historical trend for our sample period in Figure 1. In particular, we note that the sentiment variations around the burst of the Internet bubble (from the fourth quarter of 1999 to the fourth quarter of 2000) were unprecedented. Both the maximum and the minimum values of $\Delta SENTIMENT^{\perp}$ around the burst were much larger in magnitude than the previous 20-year high and low.

As pointed out by Baker and Wurgler (2006, 2007), a stylized fact about investor sentiment is that, although its impact on stock prices is not persistent over time, a period of extraordinary investor sentiment is usually associated with events that can push prices to an unreasonably high or low level. In this spirit, Figure 1 provides a brief description of 11 quarters (top decile in our sample) with the highest sentiment variation. All of these quarters are associated with significant events that are striking enough to earn their names. For example, the four quarters ranked at the top are associated with the Internet bubble (1999Q4) and its burst (2000Q4), the subprime mortgage crisis (2007Q4), and the 9/11 attack (2001Q3). Not surprisingly, $\Delta SENTIMENT^{\perp}$ for these quarters is either significantly positive or negative. It reaches 4.21 in the

[10] The market-wide sentiment variation *within* each quarter should be captured by the standard deviation of $\Delta SENTIMENT^{\perp}$ or the sum of absolute value of monthly $\Delta SENTIMENT^{\perp}$. However, using variation within each quarter will generate confusing results. For example, if the market-wide sentiment significantly increases at the beginning of the quarter and returns to its previous level by the end of the quarter, the market-wide sentiment variation of the quarter is zero, but the variation within the quarter is large. Obviously, in this case, it is very likely that mispricing driven by the sentiment effect has been corrected within the quarter and will have no impact on future stock returns.

Table 1 Summary Statistics

	All firms	Quintiles 2–5 firms	Quintile 5 (largest) firms	Quintile 4 firms	Quintile 3 firms	Quintile 2 firms	Quintile 1 (smallest) firms
$BREADTH_t$ (%)							
Mean	1.12	2.01	5.70	2.27	1.26	0.72	0.24
Std.	1.88	2.34	3.34	1.26	0.78	0.48	0.24
$\Delta BREADTH_t$ (%)							
Mean	0.02	0.03	0.09	0.03	0.02	0.01	−0.00
Std.	0.24	0.33	0.63	0.33	0.22	0.15	0.07
$HOLD_t$ (%)							
Mean	12.22	15.97	16.83	17.62	16.30	14.44	8.50
Std.	11.49	12.37	11.48	12.82	12.74	12.07	9.14
$\Delta HOLD_t$ (%)							
Mean	0.24	0.35	0.22	0.31	0.42	0.39	0.13
Std.	2.29	2.44	1.84	2.43	2.58	2.59	2.11
$LOGSIZE_t$							
Mean	5.374	6.771	8.838	7.458	6.522	5.634	3.989
Std.	1.834	1.351	0.953	0.654	0.643	0.682	1.020
BK/MKT_t							
Mean	0.711	0.610	0.566	0.600	0.605	0.637	0.812
Std.	0.539	0.431	0.405	0.434	0.423	0.444	0.611
$NYSE/AMEX\ TURNOVER_t$ (%)							
Mean	22.1	25.5	24.7	27.9	26.3	23.2	14.7
Std.	24.5	25.7	20.7	26.6	28.1	26.3	19.6
$NASDAQ\ TURNOVER_t$ (%)							
Mean	36.4	52.8	86.8	64.0	54.5	46.4	28.2
Std.	43.0	52.4	60.8	58.8	53.4	47.7	34.4
$MOM12_t$ (%)							
Mean	20.1	28.0	25.7	28.1	29.6	27.9	12.2
Std.	76.3	76.6	58.9	79.0	79.4	80.3	75.2
No. of obs	344,412	171,480	28,703	34,961	44,257	63,559	172,932

Notes. The sample includes stocks from the NYSE, AMEX, and NASDAQ between the second quarter of 1980 and the fourth quarter of 2007. Independent variables are defined following Chen et al. (2002)—i.e., $BREADTH_t$ is the fraction of all mutual funds that hold long positions in the stock at the end of quarter t; $\Delta BREADTH_t$ is the change in breadth of mutual fund ownership for a stock in quarter t; $HOLD_t$ is the fraction of shares outstanding of a stock held by mutual funds at the end of quarter t; $\Delta HOLD_t$ is the change in aggregate mutual fund holdings of a stock ($HOLD_t$) in quarter t; $LOGSIZE_t$ is the log of market capitalization at the end of quarter t; BK/MKT_t is the most recently available observation of book-to-market ratio before the end of quarter t; $NYSE/AMEX\ TURNOVER_t$ is the share turnover in quarter t among stocks listed on the NYSE and AMEX; $NASDAQ\ TURNOVER_t$ is the share turnover in quarter t among stocks listed on NASDAQ; $XTURNOVER_t$ is the share turnover demeaned within each quarter by the average turnover for the firm's stock exchange; and $MOM12_t$ is the raw return from the beginning of quarter $t-3$ to the end of quarter t. Size quintiles are determined using NYSE breakpoints.

fourth quarter of 1999 and then drops to −5.71 in the fourth quarter of 2000, which reflects the volatile sentiment variation during the Internet bubble formation and burst periods.

3.3. Summary Statistics

Table 1 provides summary statistics of all variables used in our study. Following Chen et al. (2002), we partition the sample into quintiles based on the NYSE breakpoints. Although our sample period is longer than that of Chen et al. (2002), the main statistical patterns of our key variables remain very similar to theirs. Despite many similarities, however, our sample exhibits two obvious differences. First, the average level of $BREADTH_t$ is lower, and the average level of $HOLD_t$ is higher than the one for the earlier sample. Specifically, the average level of $BREADTH_t$ ($HOLD_t$) in our sample is 1.12% (12.22%), compared with 1.29% (8.58%) for the sample period in Chen et al. (2002). This observation is driven mainly by the increased number and holdings of mutual funds after 1998. Second, the turnovers of stocks in both the NASDAQ and NYSE/AMEX markets surge significantly. This result coincides with the tremendous increase of trading activities around the burst of the Internet bubble in 2000.

4. Investment Sentiment and Return Predictiveness of $\Delta BREADTH_t$

4.1. Testing Hypothesis 1

Hypothesis 1 focuses on the impact of time-series variations in market-wide sentiment variations—σ_S^2 in Equation (17)—on the breadth–return relationship. Specifically, if we partition all quarters in our sample into two groups according to the level of market-wide sentiment variation, we expect a positive breadth–return relationship in the low-sentiment-variation group, and we expect a less positive or even negative breadth–return relationship in the high-sentiment-variation group. In this section, we test

Hypothesis 1 by portfolio sorts and Fama–MacBeth regressions.

4.1.1. Portfolio Sorts. Our empirical strategy in portfolio sorts is identical to Chen et al. (2002) and is summarized as follows. In each quarter t, we first sort all stocks into size quintiles using the NYSE breakpoints and drop all firms in the smallest size quintile. All remaining stocks in our sample are ranked into decile classes based on $\Delta BREADTH_t$, with decile breakpoints determined separately within each size quintile. We then recombine the deciles across size classes. An equally weighted portfolio is formed in each $\Delta BREADTH_t$ decile group, and the performance of portfolios is measured in one quarter. As argued by Chen et al. (2002, p. 193), this procedure rules out the possibility that "the extreme $\Delta BREADTH_t$ deciles would be dominated by large stocks." Furthermore, to ensure that our results are not driven by firm characteristics that have known effects on cross-sectional return patterns, we adjust raw returns of all stocks by size, book-to-market, and momentum effects, following Daniel et al. (1997) and Chen et al. (2002).

Results in Table 2 suggest that, for the full sample, the raw one-quarter hedging portfolio return from simultaneously holding a long position of stocks in the highest $\Delta BREADTH_t$ decile ($P10$) and a short position of stocks in the lowest $\Delta BREADTH_t$ decile ($P1$) is only 1.32%, which is statistically significant at the 10% level. Consistent with Nagel (2005), when the raw hedging portfolio return is adjusted by size, book-to-market, and momentum effects, we find that its magnitude decreases to 0.42% and is no longer statistically significant.

To test Hypothesis 1, we partition all quarters in our sample into two groups based on the proxy for the time-series variation of market-wide sentiment—i.e., $|\Delta SENTIMENT^{\perp}|$, the absolute level of $\Delta SENTIMENT^{\perp}$. Specifically, the low-sentiment-variation sample consists of 100 quarters in the

Table 2 **Returns to Portfolio Strategies Based on $\Delta BREADTH$ and $|\Delta SENTIMENT^{\perp}|$**

	Raw three-month return			Size/book-to-market/momentum-adjusted return		
ΔBREADTH deciles	All	Low sentiment variation	High sentiment variation	All	Low sentiment variation	High sentiment variation
1 (lowest)	3.15%	2.60%	8.16%	−0.05%	−0.30%	2.18%
	(2.49)	(2.13)	(1.27)	(−0.24)	(−1.57)	(1.64)
2	3.02%	2.83%	4.73%	−0.41%	−0.43%	−0.19%
	(3.11)	(2.91)	(1.09)	(−2.43)	(−2.60)	(−0.23)
3	3.76%	3.59%	5.26%	0.01%	−0.03%	0.37%
	(4.28)	(4.00)	(1.49)	(0.10)	(−0.20)	(0.50)
4	3.37%	3.37%	3.38%	−0.19%	−0.23%	0.20%
	(3.99)	(3.85)	(1.05)	(−1.29)	(−1.63)	(0.27)
5	3.19%	3.20%	3.10%	−0.23%	−0.22%	−0.41%
	(3.86)	(3.73)	(0.97)	(−1.66)	(−1.52)	(−0.61)
6	3.76%	3.78%	3.64%	0.01%	−0.00%	0.15%
	(4.72)	(4.56)	(1.23%)	(0.11)	(−0.00)	(0.33)%
7	3.63%	3.62%	3.72%	−0.09%	−0.04%	−0.60%
	(4.39)	(4.31)	(1.05)	(−0.76)	(−0.28)	(−2.79)
8	3.93%	3.88%	4.32%	0.02%	0.04%	−0.11%
	(4.34)	(4.21)	(1.14)	(0.18)	(0.29)	(−0.28)
9	4.26%	4.26%	4.28%	0.31%	0.34%	0.11%
	(4.16)	(4.12)	(0.94)	(2.22)	(2.65)	(0.13)
10 (highest)	4.47%	4.58%	3.46%	0.37%	0.51%	−0.84%
	(3.93)	(4.01)	(0.67)	(1.56)	(2.22)	(−0.68)
$P10-P1$	1.32%	1.98%	−4.70%	0.42%	0.81%	−3.02%
	(1.83)	(3.50)	(−1.38)	(1.10)	(2.53)	(−1.83)
No. of quarters	111	100	11	111	100	11

Notes. Portfolio strategies based on $\Delta BREADTH_t$ are carried out in a sample from 1980Q2 to 2007Q4 (111 quarters in total). We include stocks from the NYSE, AMEX, and NASDAQ with a market capitalization above the 20th percentile using NYSE breakpoints. In each quarter t, stocks are ranked into deciles according to $\Delta BREADTH$ relative to other stocks in their size quintiles. An equally weighted portfolio is formed in each decile, and the portfolio returns are computed over one quarter. Portfolio returns are adjusted by size, book-to-market, and momentum effects following Daniel et al. (1997) and Chen et al. (2002). The table reports the average raw and adjusted returns of portfolios in each $\Delta BREADTH$ decile and those in two subgroups sorted by a measure capturing the time-series variation of market-wide sentiment. The high-sentiment-variation group includes 11 quarters that have the highest absolute levels of $\Delta SENTIMENT^{\perp}$ as defined in Baker and Wurgler (2007). The low-sentiment-variation group represents the remaining 100 quarters. The t-statistics, which are in parentheses, are adjusted for serial-correlation using a Newey–West estimator (Newey and West 1987) with one lag for the raw and size/book-to-market/momentum-adjusted returns over one quarter.

first nine deciles of $|\Delta SENTIMENT^{\perp}|$, and the high-sentiment-variation sample consists of 11 quarters in the decile with the largest value of $|\Delta SENTIMENT^{\perp}|$. We start with this asymmetric partition because it reflects two well-known characteristics of investor sentiment. First, investor sentiment is not a persistently dominant force in the financial market. For example, we cannot simply adopt an equal partition because it is hard to imagine that investor sentiment variation would dominate stock price changes in one out of every two quarters for our 28-year sample period. Second, investor sentiment is usually associated with specific asset bubbles, market crashes, or other striking events. As discussed in §3.2, the 11 quarters with the highest $|\Delta SENTIMENT^{\perp}|$ do capture major sentiment-related events well. We will discuss alternative partition methods in §4.1.3.

Results reported in Table 2 suggest that the time-series variation in market-wide investor sentiment has a significant impact on the breadth–return relationship. For the high-sentiment-variation group, the average raw return of $P1$ (stocks with the lowest $\Delta BREADTH_t$ in each size quintile) is 8.16%, which is 4.70% (in magnitude) higher than that of $P10$ (stocks with the highest $\Delta BREADTH_t$ in each size quintile). Moreover, the average adjusted return of $P1$ now turns positive (2.18%), whereas that of $P10$ shrinks to a negative level of -0.84%. Put differently, after adjusting for size and book-to-market and momentum effects, stocks in $P1$ outperform those in $P10$ by 3.02% in one quarter. As predicted by Hypothesis 1, this result suggests that, in the high-sentiment-variation group, the change of ownership breadth is mainly a proxy for the variation of investor sentiment instead of the variation of short-sales constraints. Therefore, a stock with a significant increase (decrease) of ownership breadth is likely to be overvalued (undervalued), and a future market correction will lead to a negative breadth–return relationship. It is important to point out that the positive predictive power of $\Delta BREADTH_t$ for future stock returns in Chen et al. (2002) would still hold for the remaining 100 quarters in the low-sentiment-variation group. Specifically, in these quarters, the raw (adjusted) one-quarter hedging portfolio return is 1.98% (0.81%), which is statistically significant at the 1% (5%) level.

4.1.2. Fama–MacBeth Regressions. Results from portfolio sorts provide preliminary supportive evidence for Hypothesis 1. However, this technique has three limitations. First, considerable variations in each sorting variable (such as $\Delta BREADTH_t$) might still exist across firms in each sorted portfolio (group). Second, it is difficult to consider other risk and firm-characteristic components at the same time (i.e., we usually cannot go beyond three-way sorts). Third, with portfolio sorts, we are not able to identify the quantitative impacts of $|\Delta SENTIMENT^{\perp}|$ on the return predictiveness of $\Delta BREADTH_t$ precisely. Therefore, we perform Fama–MacBeth (1973) regression tests to complement our previous results.

In Fama–MacBeth regressions, the dependent variable is measured in units of raw returns, because all firm characteristics that may affect future stock returns can be controlled as independent variables in the regression. Our specification is identical to that used in column (4) of Table 6 in Chen et al. (2002):

$$\begin{aligned} Ret_{i,\,t+1} = \alpha_t &+ \beta_1 \times \Delta BREADTH_{i,\,t} + \beta_2 \times \Delta HOLD_{i,\,t} \\ &+ \beta_3 \times \Delta LOGSIZE_{i,\,t} + \beta_4 \times BK/MKT_{i,\,t} \\ &+ \beta_5 \times XTURNOVER_{i,\,t} + \varepsilon_t, \end{aligned} \tag{18}$$

where $Ret_{i,\,t+1}$ represents one-quarter-ahead raw returns for stock i.

It is important to point out that the Fama–MacBeth regressions used in Chen et al. (2002) are slightly different from the standard ones in the literature. That is, for the specification outlined in Equation (18), we run a separate cross-sectional regression every quarter for every size class. We first average the coefficients across size classes for each quarter, and the standard errors are then computed based on time-series serial correlation properties of average coefficients for all quarters. These regressions are conducted separately for low- and high-sentiment-variation groups defined in the previous section. We compare β_1s from low- and high-sentiment-variation groups to conclude how the variation of market-wide sentiment affects the breadth–return relationship.

Table 3 reports the means and t-statistics of coefficients from Fama–MacBeth regressions. We find that the predictive power of $\Delta BREADTH_t$ for future stock returns has largely disappeared in the entire sample from 1980Q2 to 2007Q4. The coefficient β_1 reported in column (1) equals 0.509 with a marginally significant t-statistic of 1.86. Results based on group partitions confirm our findings in portfolio sorts. The coefficient of $\Delta BREADTH_t$ suggests that the positive breadth–return relationship is not only weakened but also reversed when the level of $|\Delta SENTIMENT^{\perp}|$ is high. Specifically, β_1 equals -1.124 in the regression for the high-sentiment-variation group, whereas β_1 is 0.688 in the regression for the low-sentiment-variation group. These results present a sharp contrast to the breadth–return relationship between the two groups. The difference between β_1 for the two groups is as large as 1.812 and is statistically significant at the 5% level.

Obviously, the results from the Fama–MacBeth regressions support Hypothesis 1, which states that, when the time-series variation of market-wide investor sentiment is large enough to exert an

Table 3 **Forecasting Returns with $\Delta BREADTH$ and $|\Delta SENTIMENT^{\perp}|$**

	Raw three-month return		
	(1)	(2)	(3)
Variables	All	Low sentiment variation	High sentiment variation
$\Delta BREADTH_t$	0.509	0.688	−1.124
	(1.86)	(2.86)	(−0.67)
$\Delta HOLD_t$	0.013	0.024	−0.088
	(0.37)	(0.65)	(−0.83)
$LOGSIZE_t$	−0.001	0.000	−0.015
	(−0.82)	(0.10)	(−2.00)
BK/MKT_t	0.016	0.016	0.013
	(2.68)	(2.56)	(0.76)
$MOM12_t$	0.019	0.023	−0.023
	(4.13)	(5.42)	(−1.10)
$XTURNOVER_t$	−0.026	−0.030	0.010
	(−2.33)	(−2.53)	(0.30)
No. of quarters	111	100	11
Avg. adj. R^2	0.065	0.062	0.094
$Diff\,(\Delta BREADTH_t)$: low–high		1.812	
t-statistic		(2.01)	

Notes. Fama–MacBeth regressions are carried out in a sample that includes stocks from the NYSE, AMEX, and NASDAQ with a market capitalization above the 20th percentile using NYSE breakpoints from 1980Q2 to 2007Q4. The test specification is identical to that in Chen et al. (2002)—i.e., we run a separate cross-sectional regression every quarter for each size group. We average the coefficients across size classes for each quarter. The standard errors are then based on the time-series serial-correlation properties of these estimates. The dependent variable is the raw return over one quarter. Among independent variables, $\Delta BREADTH_t$ is the change in breadth of mutual fund ownership for a stock in quarter t, $\Delta HOLD_t$ is the change in aggregate mutual-fund holdings of a stock ($HOLD_t$) in quarter t, $LOGSIZE_t$ is the log of market capitalization at the end of quarter t, BK/MKT_t is the most recently available observation of book-to-market ratio at the end of quarter t, $MOM12_t$ is the raw return from the beginning of quarter $t-3$ to the end of quarter t, and $XTURNOVER_t$ is the share turnover demeaned within each quarter by the average turnover for the firm's stock exchange. We also provide results in two subperiods sorted by a measure capturing the time-series variation of market-wide sentiment. The high-sentiment-variation group includes 11 quarters that have the highest absolute levels of $\Delta SENTIMENT^{\perp}$ (change of sentiment) as defined in Barker and Wurgler (2007). The low-sentiment-variation group represents the remaining 100 quarters. The t-statistics of coefficients from Fama–MacBeth regressions, which are in parentheses below the corresponding coefficients, are adjusted for serial correlation and heteroskedasticity. The differences of coefficients on $\Delta BREADTH$ between the two subgroups with t-statistics are reported at the bottom.

overwhelming impact on stock prices, the otherwise positive breadth–return relationship turns negative. Our results suggest that, although we confirm the findings in Nagel (2005), the conclusions in Chen et al. (2002) still hold in the extended sample period if the impact from the time-series variation of market-wide investor sentiment is properly controlled.

4.1.3. Alternative Sample Partitions and Related Macroeconomic Factors. Our partition above—i.e., the top 10% versus the bottom 90%—provides a clear and intuitive setting to test Hypothesis 1. However, this partition may not be able to address the following concerns. First, the cut-off levels of partitions largely depend on how broadly we define sentiment-driven events. If we give a broader definition of sentiment-driven events, more quarters should be included in the high-sentiment-variation group. Second, the two-group partition in previous tests does not allow us to test whether the breadth–return relationship is continuously and monotonically affected by the time-series variation in market-wide investor sentiment, especially within each group. Third, the partition method cannot detect whether the breadth–return relationship is affected by time-series variations of other macroeconomic factors that may be highly correlated with the variation of market-wide investor sentiment. We address these concerns with the following tests.

In our first test, we sort all quarters into quintiles according to $|\Delta SENTIMENT^{\perp}|$, and we report the raw and adjusted hedging portfolio returns as well as the coefficient β_1 from the Fama–MacBeth regressions for each quintile in Table 4. With 23 quarters in the highest-sentiment-variation quintile, the raw and adjusted hedging portfolio returns based on $\Delta BREADTH$ and the Fama–MacBeth coefficient β_1 are still negative. However, compared with those in the top $|\Delta SENTIMENT^{\perp}|$ decile (high-sentiment-variation group reported in Tables 2 and 3), their magnitude and statistical significance are reduced. More important, the raw and adjusted hedging portfolio returns based on $\Delta BREADTH$ strategy as well as the Fama–MacBeth coefficients of $\Delta BREADTH$ in predicting future returns are monotonically decreasing when the variation of market-wide sentiment increases. Further, the differences of average raw and adjusted hedging portfolio returns between the low-sentiment-variation quintile and the high-sentiment-variation quintile are 4.95% and 2.85%, which are statistically significant

Table 4 Alternative Sample Partitions

$\vert \Delta SENTIMENT^{\perp} \vert$ group	1 (low)	2	3	4	5 (high)	Low-high
$P10$–$P1$ based on $3M$ raw return	2.85%	2.33%	2.16%	1.49%	−2.10%	4.95%
	(1.89)	(2.04)	(1.86)	(1.24)	(−1.18)	(1.87)
$P10$–$P1$ based on $3M$ adj. return	1.49%	1.19%	0.69%	0.22%	−1.36%	2.85%
	(2.78)	(2.55)	(1.19)	(0.59)	(−1.29)	(2.06)
Fama–MacBeth coef. of $\Delta BREADTH_t$	1.089	0.815	0.802	0.467	−0.581	1.670
	(1.74)	(1.68)	(1.24)	(1.48)	(−0.70)	(1.69)
No. of quarters	22	22	22	22	23	—

Notes. Our sample includes all stocks from the NYSE, AMEX, and NASDAQ with a market capitalization above the 20th percentile using NYSE breakpoints from 1980Q2 to 2007Q4. We partition all 111 quarters into five groups according to $|\Delta SENTIMENT^{\perp}|$. The average hedging portfolio returns, adjusted hedging portfolio returns (similar to those reported in Table 2), and the coefficients of $\Delta BREADTH_t$ (similar to those reported in Table 3) are reported for each $|\Delta SENTIMENT^{\perp}|$ group. The t-statistics for the raw and adjusted hedging portfolio returns, which are in parentheses, are adjusted for serial correlation using a Newey–West estimator with one lag. We also report the differences of average raw and adjusted hedging portfolio returns between the lowest-sentiment-variation quintile and the highest-sentiment-variation quintile with t-statistics.

at the 10% and 5% levels, respectively. These results not only confirm the economic intuition underlying Equation (17) but also distinguish our theory-based empirical findings from that in Nagel (2005). That is, the impact of market-wide sentiment variations on the breadth–return relationship is indeed continuous and monotonic. These results suggest that our previous findings do not depend on specific cut-off levels in sample partitions.

In our second test, we gradually increase the number of removed quarters based on the rank of $|\Delta SENTIMENT^{\perp}|$.[11] Specifically, we start with the entire sample of 111 quarters and remove the quarter with the highest sentiment variation. Then we remove the quarters with the second and third highest sentiment variations, etc. Untabulated results exhibit three main features. First, the quarter with the highest sentiment variation (2000Q4) has an enormous impact on the return–breadth relationship. After removing this single quarter from our sample, we find that the (adjusted) hedging portfolio return based on $\Delta BREADTH$ increases from 1.32% (0.42%) to 1.58% (0.61%), which is statistically significant at the 5% (10%) level. Second, in spite of its great impact, the negative breadth–return relationship is not only driven by the quarter with the highest sentiment variation. As we increase the number of removed quarters based on the rank of sentiment variations, both the raw and adjusted hedging portfolio returns gradually increase. Third, as we remove more quarters, the average raw (adjusted) hedging portfolio return improves at a decreasing speed.

In our third test, we focus on alternative macroeconomic factors that may also explain the breadth-return relationship. We first obtain the coefficient of $\Delta BREADTH_t$ (β_1 in §4.1.2) for each quarter t from our Fama–MacBeth regressions. Then we place β_1 as the dependent variable in the following ordinary least squares regression:

$$\beta_{1,t} = \mu + \gamma_1 \times Sentiment\ Proxy_t + \sum_{k=0}^{n} \gamma_k \times control_{k,t} + \varepsilon_t. \quad (19)$$

The sentiment proxy consists of the level of sentiment, the change of sentiment level, or their absolute values. The controls consist of those macroeconomic variables discussed in §3.1.

Table 5 presents the coefficients and t-statistics from the estimation of Equation (19). We start with four univariate regressions with alternative sentiment proxies, including the *level* of investor sentiment ($SENTIMENT^{\perp}$), the *absolute level* of investor sentiment ($|SENTIMENT^{\perp}|$), the *change* of investor sentiment ($\Delta SENTIMENT^{\perp}$), and the *absolute change* of investor sentiment ($|\Delta SENTIMENT^{\perp}|$). Based on β_1 from the Fama–MacBeth regressions, our results suggest, that in predicting one-quarter-ahead raw returns, the negative breadth–return relationship is significantly associated with the absolute change of investor sentiment ($\gamma_1 = -0.685$ with a t-statistic of -2.35, in column (4)). However, it is not affected by the level of sentiment ($\gamma_1 = 0.087$ with a t-statistic of 0.22, in column (1)), the absolute level of sentiment ($\gamma_1 = -0.083$ with a t-statistic of -0.16, in column (2)), or the change of investor sentiment ($\gamma_1 = 0.350$ with a t-statistic of 1.55, in column (3)). Consistent with Proposition 2, we show that what really matters for the breadth–return relationship is the variation rather than the level or the signed change of market-wide sentiment.

In column (5), we add macroeconomic variables that may have an impact on the predictive power of $\Delta BREADTH_t$, including the T-bill rate ($T\text{-}Bill\ 3M_t$), the term spread ($Term\ Spread_t$), the default spread ($Default\ Spread_t$), the dividend yield ($Div\ Yield_t$), the

[11] This test is reported in Table B2 of the online appendix.

Table 5 Explaining the Breadth–Return Relationship with Sentiment Proxies and Other Macroeconomic Variables

	Coef($\Delta BREADTH$) of $Ret_{0,3}$				
	(1)	(2)	(3)	(4)	(5)
$SENTIMENT^{\perp}{}_t$	0.087				
	(0.22)				
$\lvert SENTIMENT^{\perp}{}_t \rvert$		−0.083			
		(−0.16)			
$\Delta SENTIMENT^{\perp}{}_t$			0.350		
			(1.55)		
$\lvert \Delta SENTIMENT^{\perp}{}_t \rvert$				−0.685	−0.758
				(−2.35)	(−2.51)
$T\text{-}Bill\ 3M_t$					0.450
					(1.86)
$Term\ Spread_t$					0.608
					(1.62)
$Default\ Spread_t$					0.615
					(0.62)
$Div\ Yield_t$					−1.144
					(−1.88)
$GDP\ Growth_t$					0.015
					(0.15)
Inflation					0.013
					(0.12)
Adj. R^2	−0.009	−0.009	0.028	0.040	0.029
No. of quarters	111	111	111	111	111

Notes. Our sample includes all stocks from the NYSE, AMEX, and NASDAQ with a market capitalization above the 20th percentile using NYSE breakpoints from 1980Q2 to 2007Q4. The dependent variable in the regressions reported in this table is the coefficient of $\Delta BREADTH$ in Fama–MacBeth regression to predict future three-month returns (i.e., those reported in Table 3). $SENTIMENT^{\perp}$ and $\Delta SENTIMENT^{\perp}$ are the sentiment measure and the change-of-sentiment measure of quarter t as defined in Baker and Wurgler (2007). $\lvert SENTIMENT^{\perp}\rvert$ and $\lvert\Delta SENTIMENT^{\perp}\rvert$ are the absolute values of $SENTIMENT^{\perp}$ and $\Delta SENTIMENT^{\perp}$, respectively. $T\text{-}Bill\ 3M_t$ is the annualized three-month T-bill yield in quarter t, $Term\ Spread_t$ is the difference between the average annualized 10-year T-bond yield and average annualized three-month T-bill yield in quarter t, $Default\ Spread_t$ is the difference between the average yield of bonds rated Baa by Moody's and the average yield of bonds rated Aaa by Moody's in quarter t, and $Div\ Yield_t$ is the defined as the annualized difference between the CRSP value-weighted index return with distribution and the one without distribution in quarter t. $GDP\ Growth_t$ is the annualized real GDP growth rate in quarter t, based on 2005 dollars. $Inflation_t$ is the annualized growth rate of the consumer price index in quarter t. The t-statistics, which are in parentheses, are adjusted for serial correlation and heteroskedasticity.

GDP growth rate ($GDP\ Growth_t$), and the inflation rate ($Inflation_t$). After incorporating these macroeconomic variables, the coefficient of $\lvert\Delta SENTIMENT^{\perp}\rvert$ remains statistically significant at the 5% level, and its magnitude is even larger than that in the univariate regression. Only two macroeconomic variables ($T\text{-}Bill\ 3M$ and $Div\ Yield$) are marginally significant at the 10% level. After adding these macroeconomic independent variables, the adjusted R^2 of the regression is reduced, and the magnitude and statistical significance of the coefficient for $\lvert\Delta SENTIMENT^{\perp}\rvert$ is not reduced. These results suggest that macroeconomic variables are not likely to play roles similar to that of the variation of market-wide sentiment in explaining the return predictiveness of $\Delta BREADTH_t$.

4.2. Testing Hypothesis 2

As discussed above, the time-series variation in market-wide sentiment triggers systematic mispricing and makes a significantly increased (decreased) breadth of ownership a good proxy for investor optimism (pessimism). However, if all stocks in one time period react to market-wide sentiment variations in the same manner, we will not be able to detect the difference of the change in ownership breadth driven by the market-wide sentiment variations at the individual stock level. If that is true, we cannot observe sufficient cross-sectional variations of the change in ownership breadth to test the breadth–return relationship. Therefore, conditional on a high variation of market-wide sentiment, Hypothesis 2 states that the negative breadth–return relationship would be more significant when there exists a larger dispersion in firm-specific exposure to market-wide sentiment variation (σ^2_{bS} in Equation (17)) in the cross section.

4.2.1. Sentiment Beta. To test Hypothesis 2, we compute the sentiment beta, which was first introduced by Baker and Wurgler (2007), as a proxy for the firm-specific exposure to market-wide sentiment variation. Specifically, in addition to the Fama and French (1993) three factors and the Carhart (1997) momentum factor, we include $\Delta SENTIMENT^{\perp}$, market sentiment changes, as the fifth factor in Equation (20), and we estimate loadings of all factors with monthly data. β_{SENT}, the loading on $\Delta SENTIMENT^{\perp}$, measures the sensitivity of individual stock returns to market sentiment changes. For each stock i, the sentiment beta is defined by $\beta_{SENT,i}$ estimated for the entire sample period (i.e., from 1980Q2 to 2007Q4) as follows:[12]

$$\begin{aligned} r_{i,t} - r_{f,t} &= \beta_{MKT,i} \times (r_{MKT,t} - r_{f,t}) + \beta_{SMB,i} \times r_{SMB,t} \\ &\quad + \beta_{HML,i} \times r_{HML,t} + \beta_{UMD,i} \times r_{UMD,t} \\ &\quad + \beta_{SENT,i} \times \Delta SENTIMENT^{\perp}_t + \varepsilon_i. \end{aligned} \tag{20}$$

Our estimation shows that sentiment beta, β_{SENT}, has a symmetric distribution around zero with two fat tails. We partition all stocks in the cross section into four groups according to β_{SENT} and compute the panel mean of firm characteristics within each group.[13] We find that stocks with extremely high or

[12] In this test, we require that each stock survive for at least 30 months for a reliable estimate of β_{SENT}. Similar to the sentiment beta in Baker and Wurgler (2007), because it is estimated in the full sample, we regard sentiment beta as a firm characteristic with no time-series variations in this paper.

[13] We first compute the annual means of firm characteristics for each group and then take the time-series average.

Table 6 **Returns to Portfolio Strategies Based on $\Delta BREADTH$, Sentiment Beta, and $|\Delta SENTIMENT^{\perp}|$**

	All		Low-sentiment-variation quarters		High-sentiment-variation quarters	
$\Delta BREADTH$	Small β_{SENT} dispersion	Large β_{SENT} dispersion	Small β_{SENT} dispersion	Large β_{SENT} dispersion	Small β_{SENT} dispersion	Large β_{SENT} dispersion
Raw three-month return						
1 (lowest)	3.32%	3.11%	2.96%	2.45%	6.60%	9.12%
	(2.64)	(2.41)	(2.41)	(1.98)	(1.05)	(1.39)
2–9	3.83%	3.67%	3.78%	3.57%	4.26%	4.57%
	(4.64)	(3.88)	(4.43)	(3.71)	(1.35)	(1.13)
10 (highest)	4.58%	4.36%	4.64%	4.55%	4.08%	2.61%
	(4.13)	(3.64)	(4.10)	(3.80)	(0.88)	(0.47)
10–1	1.26%	1.25%	1.68%	2.10%	−2.52%	−6.51%
	(1.86)	(1.07)	(2.90)	(3.41)	(−0.64)	(−1.74)
Adj. three-month return						
1 (lowest)	−0.13%	−0.02%	−0.27%	−0.33%	1.17%	2.81%
	(0.17)	(0.44)	(−0.27)	(−1.00)	(0.55)	(2.52)
2–9	−0.02%	−0.01%	−0.01%	−0.00%	−0.07%	−0.04%
	(−0.13)	(−0.08)	(−0.08)	(−0.04)	(−0.21)	(−0.13)
10 (highest)	0.38%	0.35%	0.45%	0.57%	−0.27%	−1.63%
	(1.26)	(1.26)	(1.44)	(1.96)	(−0.25)	(−0.99)
10–1	0.51%	0.37%	0.72%	0.90%	−1.44%	−4.44%
	(1.21)	(0.81)	(1.85)	(2.83)	(−0.79)	(−2.10)
No. of quarters	111		100		11	

Notes. Portfolio strategies based on $\Delta BREADTH$ are carried out in a sample from 1980Q2 to 2007Q4. We include stocks from the NYSE, AMEX, and NASDAQ with a market capitalization above the 20th percentile using NYSE breakpoints. We first compute the sentiment beta β_{SENT} in the following model for each stock i in the full sample: $r_{i,t} - r_{f,t} = \beta_{MKT,i} \times (r_{MKT,t} - r_{f,t}) + \beta_{SMB,i} \times r_{SMB,t} + \beta_{HML,i} \times r_{HML,t} + \beta_{UMD,i} \times r_{UMD,t} + \beta_{SENT,i} \times \Delta SENTIMENT_t^{\perp} + \varepsilon_i$. In each quarter t, stocks are ranked into four groups according to β_{SENT}. Stocks in the lowest and highest quartiles are defined as those with large sentiment-beta dispersion; stocks in the second and third quartiles are defined as those with small sentiment-beta dispersion. Independently, stocks are ranked into deciles according to $\Delta BREADTH$ relative to other stocks in their size quintiles. For simplicity, we combine the stocks within the second and ninth $\Delta BREADTH$ deciles into one group (denoted as 2–9 in the table). The table reports the average raw (upper panel) and adjusted equal-weight returns (lower panel) of portfolios in each $\Delta BREADTH$-β_{SENT} group. In addition to the entire sample period, we provide results in two subperiods sorted by a measure capturing the time-series variation of market-wide sentiment. The high-sentiment-variation group includes 11 quarters that have the highest absolute levels of $\Delta SENTIMENT^{\perp}$ as defined in Baker and Wurgler (2007). The low-sentiment-variation group represents the remaining 100 quarters. The t-statistics, which are in parentheses, are adjusted for serial correlation using a Newey–West estimator with one lag for the raw and size/book-to-market/momentum-adjusted returns over one quarter.

low sentiment betas (i.e., those in quartiles 1 and 4) are smaller in firm size, lower in ownership breadth, and higher in turnover than stocks with sentiment betas close to zero (i.e., those in quartiles 2 and 3). Moreover, stocks with extreme sentiment betas tend to be growth stocks and past winners. However, the average levels of the change in ownership breadth are almost the same across all sentiment-beta groups.

4.2.2. Breadth–Return Relationship for Firms with Different Sentiment Beta Dispersion. Stocks in quartiles 1 and 4 are grouped together to form the group of large sentiment-beta dispersion, and stocks in quartiles 2 and 3 enter the group of small sentiment-beta dispersion.[14] Similar to previous tests, we rank stocks independently into deciles according to $\Delta BREADTH$ relative to other stocks in their size quintiles. Because our focus is on the difference in future returns between the stocks in the first and tenth deciles of $\Delta BREADTH_t$, we combine the stocks within the second and ninth $\Delta BREADTH$ deciles into one group for simplicity. We denote it as group 2–9 in Table 6.

The first two columns of Table 6 present the return differences between the deciles with the lowest and highest change in breadth for the groups with small- and large sentiment-beta dispersion. The top panel shows that the difference in raw returns (1.26%) is marginally significant at the 10% level for the small sentiment-beta dispersion group. However, the difference (1.25%) is statistically insignificant for the large sentiment-beta dispersion. The results from adjusted three-month returns yield the same inference. Although the positive differences in adjusted returns are insignificant for both the small and large sentiment-beta dispersions, the former is about 38% higher than the latter (0.51% versus 0.37%).

[14] By construction, the group with stocks in quartiles 1 (lowest sentiment-beta quartile) and 4 (highest sentiment-beta quartile) must have a higher standard deviation of sentiment beta than the group with stocks in quartiles 2 and 3 (the two quartiles in the middle).

The last four columns of Table 6 present the return differences between the deciles with the lowest and the highest change in breadth for the samples independently sorted on the time-series variation of market-wide sentiment and the cross-sectional dispersion of sentiment beta. Our model suggests that the time-series variation of market-wide sentiment (σ_S^2 in Hypothesis 1) and cross-sectional dispersion in sentiment beta (σ_{bS}^2 in Hypothesis 2) jointly influence the breadth–return relationship. Hypothesis 2 will be supported if we find evidence that the negative breadth–return relationship is strongest among the stocks with the largest dispersion of sentiment beta when the market-wide sentiment variation is high (i.e., when we have a highest level of $\sigma_S^2\sigma_{bS}^2$). The results in the last four columns of Table 6 provide evidence consistent with our prediction. Both the top and bottom panels (raw and adjusted returns) show that the relation between breadth and returns is significantly negative for the group of stocks with a large sentiment-beta dispersion ($t = -1.74$ and -2.10, respectively) when the level of sentiment variation is high. The return difference between the deciles with the lowest and the highest change in breadth is negative but insignificant for the stocks with a small sentiment-beta dispersion and in the quarters with high variation of market sentiment. Furthermore, when the variation of market sentiment is low, sentiment-beta dispersion has little impact on the positive breadth-return relationship.[15] Consistent with Hypothesis 2, these results supports the joint effect of two factors at work.

5. Robustness Checks

To make sure that our results are stable in different specifications, we carry out various robustness checks. These results are not tabulated in the paper but are reported in Tables B1, B5, B6, and B8 in the online appendix.

5.1. Alternative Measures of Investor Sentiment, Sentiment Beta, and Change in Ownership Breadth

We consider the Michigan Consumer Sentiment Index (MCSI) as an alternative to the Baker–Wurgler sentiment measure used in this paper. Our results based on MCSI, although slightly weaker, are qualitatively similar to those under the Baker–Wurgler sentiment measure. The quantitative difference under the two measures may be driven by the fact that the Baker–Wurgler sentiment index directly captures the sentiment of *investors* in the financial market, whereas the focus of MCSI is mainly on the sentiment among *consumers* in the product market.

Given that the estimation of sentiment beta can be noisy, we also consider in our test the standardized sentiment beta—i.e., the sentiment beta scaled by its standard error. The results under the two alternative sentiment betas are largely the same.

In another robustness check, we sort the portfolios by "residual $\Delta BREADTH_t$" instead of $\Delta BREADTH_t$, where residual $\Delta BREADTH_t$ is defined as the residual in a univariate regression of $\Delta BREADTH_t$ against $\Delta HOLD_t$. Our results remain quantitatively and qualitatively similar to those based on $\Delta BREADTH_t$.

5.2. An Out-of-Sample Test: Subprime Mortgage Crisis Period (2008–2009)

The subprime mortgage crisis provides another opportunity to conduct an out-of-sample test of our empirical predictions. There exists sufficient anecdotal evidence suggesting a great level of sentiment variation during the subprime mortgage crisis period (2008–2009). According to our empirical predictions, we expect to see a negative breadth–return relationship during most quarters in this period.

We estimate the raw and hedging portfolio returns based on the $\Delta BREADTH$ strategy in the post-2007 sample. We find that they are negative in all eight quarters of 2008 and 2009. This effect is particularly strong in the third quarter of 2008, when Lehman Brothers went bankrupt, and in the first quarter of 2009 when the American Recovery and Reinvestment Act of 2009 ("stimulus bill" or "bail-out bill") was signed into law by President Barack Obama. Furthermore, the magnitudes of negative hedging portfolio returns are larger in the large sentiment-beta dispersion group than those in the small sentiment-beta dispersion group, where the sentiment betas are estimated in a preceding period from 1980 to 2007. This robustness test shows that our results not only are valid in our testing period but also are useful for policy makers and investors to interpret the breadth–return relationship in future financial crises.

6. Conclusion

We extend the one-period one-asset model in Chen et al. (2002) into a dynamic multiasset model to show that the breadth–return relationship is not always positive. Our model shows that the positive cross-sectional breadth–return relation conjectured and documented in Chen et al. (2002) will be affected by two additional sentiment-related factors, namely, the time-series variation of market-wide

[15] In the low-sentiment-variation group, the average hedging portfolio return based on $\Delta BREADTH$ is slightly higher in the high-β_{SENT}-dispersion group than in the low-β_{SENT}-dispersion group, which is probably driven by a positive correlation between β_{SENT} and the loadings on disagreement—i.e., firms that investors find more difficult to value are also more vulnerable to market sentiment. We do not incorporate the correlation between β_{SENT} and the loadings on disagreement in our model, because this correlation has little impact on our main hypotheses.

sentiment (Hypothesis 1) and the cross-sectional dispersion of firm-specific exposure to market sentiment variation (Hypothesis 2). Our theory generates two interesting empirical predictions: First, the coefficient of using changes in ownership breadth to predict future returns is related negatively to market sentiment variance. Second, conditional on a high variance of market-wide sentiment, the breadth–return relationship is more negative when there exists a larger cross-sectional dispersion of exposure to market-wide sentiment variations. Specifically, if variations in breadth and prices are mainly driven by disagreement other than the two sentiment-related factors mentioned above, an increase in ownership breadth predicts a higher future return in the cross section; in contrast, when both the time-series variation of market-wide sentiment and the cross-sectional dispersion of firm-specific exposure to market sentiment variation are large, this positive breadth–return relationship is reversed.

Using quarterly data on mutual fund holdings over the period 1980–2007, we find empirical evidence supporting the above theoretical predictions. These findings reconcile the seemingly contradictory results presented in Chen et al. (2002), Nagel (2005), and Choi et al. (2012). Although the three studies use different sample periods (Chen et al. versus Nagel) and different data sources (Chen et al. versus Choi et al.), the inconsistency can be resolved largely by introducing sentiment factors into the theories and empirics. Our theoretical framework and supporting empirical evidence suggest that the positive relation between breadth and future returns is state dependent. Our findings thus shed light on the importance of relaxing the assumption of aggregate unbiased belief in Miller's (1977) disagreement model. We illustrate how disagreement, short-sales constraints, and investor sentiment jointly determine future stock returns in the cross section.

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