Under-confidence, Pessimism and the Low-beta Anomaly

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Abstract

We investigate the effects of behavioral biases on asset returns using the concept of beta herding that measures the cross-sectional shrinkage in betas induced by investors' sentiment and overconfidence about the overall market outlook. Beta herding becomes apparent when investors are optimistic or overconfident regarding the future direction of the market whereas adverse beta herding arises (the dispersion of betas increases) once a crisis appears and uncertainty increases. It is following adverse beta herding periods when high beta stocks underperform low beta stocks, and thus the low beta anomaly disappears when adverse beta herding is considered. These effects of beta herding on beta-sorted portfolios are different from those of sentiment on assets with valuation difficulties. They are quite persistent, lasting more than two years.

Keywords: Beta; Herding; Overconfidence; Sentiment; Market Crises; Low-beta Anomaly.
JEL Classifications: C12, C31, G12, G14

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We investigate the effects of behavioral biases on asset returns using the concept of beta herding that measures the cross-sectional shrinkage in betas induced by investors' sentiment and overconfidence about the overall market outlook. Beta herding becomes apparent when investors are optimistic or overconfident regarding the future direction of the market whereas adverse beta herding arises (the dispersion of betas increases) once a crisis appears and uncertainty increases. It is following adverse beta herding periods when high beta stocks underperform low beta stocks, and thus the low beta anomaly disappears when adverse beta herding is considered. These effects of beta herding on beta-sorted portfolios are different from those of sentiment on assets with valuation difficulties. They are quite persistent, lasting more than two years.

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1. Introduction

The classical capital asset pricing model (CAPM) suggests that cross-sectional asset returns are solely determined by betas. However, empirical studies show little evidence of positive relation between betas and returns (Fama and French, 1992), or even an inverse relation between betas and risk-adjusted returns (Baker, Bradley, and Wurgler, 2011; Baker, Bradley, and Taliaferro, 2014). Under some circumstances, the difference between betas may be unclear or excessively large, and thus the risk-return relations may appear differently.

In this study, we demonstrate that this happens by changes in investors' sentiment and confidence about their overall market outlook, the two well-known behavioral biases in finance (Lakonishok, Shleifer, and Vishny, 1994; Barberis, Schleifer, and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998, 2001; Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012; Antoniou, Doukas, and Subrahmanyam, 2016). When investors are overconfident about signals of market outlook, their posterior prediction of the market return is affected too much by the signals as in Daniel, Hirshleifer and Subrahmanyam (1998, 2001) (DHS). For investors who use this biased market outlook to predict individual asset returns, the cross-sectional difference in the expected returns and betas decreases because it is suppressed by their overconfidence about the market outlook. A comparable shrinkage in the dispersion of betas arises in the presence of investor sentiment. When optimistic views are prevalent in the market, then individual betas will be biased towards the market beta. The opposite case also arises: when investors are under-confident about market outlook or their sentiment is pessimistic, the difference between betas increases.

This type of cross-sectional bias in betas is called "beta herding" in this study because, when investors' market outlook is affected by their behavioral biases, individual betas are biased (herd) towards the market beta regardless of their underlying equilibrium risk-return relationship. Beta herding, which we estimate by the cross-sectional variance of individual betas, measures the degree to which investors' collective estimates of individual betas are biased towards unity. It represents the outcome of investors' irrational behavior that follows the market buying or selling individual assets.[1] When adverse beta herding arises, cross-sectional asset pricing by beta becomes also biased as the difference between betas becomes excessively large.

The empirical questions we investigate are if the difference between betas changes over time, whether cross-sectional asset prices are affected by beta herding, and when this bias arises. We quantify beta herding in the equity US market over the period from January 1967 to June 2016. Our measure of beta herding is robust to macro factors, business cycle, and on average to stock market movements, but is heavily affected by the advent of crises.

We find that the cross-sectional relation between stock returns and betas is significantly affected by beta herding: low beta stocks outperform high beta stocks following adverse beta herding. The results are consistent with the low-beta anomaly of Baker, Bradley, and Wurgler (2011) and Baker, Bradley, and Taliaferro (2014), because negative risk-adjusted returns of high-minus-low beta portfolios increase as the difference between betas increases. For example, the post-formation buy-and-hold risk-adjusted return of the high-minus-low decile portfolios

[1] The term of irrational here refers to the market, as opposed to individual irrationality. We recognize that there will be situations in which it may be myopically rational for an individual to follow the herd and hence our use of irrational may seem inappropriate. However, given that such behavior may lead to inefficient asset prices and irrational behavior for the market as a whole, we will throughout this paper refer to herding simply as irrational. See Hirshleifer and Teoh (2009) and Park and Sabourian (2011) for further discussion.

formed on the betas from the Fama-French five-factor model is significant and negative, i.e., -5.97% per year. However, it becomes -17.12% per year following an adverse herding state whereas it is not significant following other states. The post-formation beta of the high-minus-low beta portfolio is 0.95 following adverse beta herding, whereas it is only 0.27 following beta herding. Considering that the post-formation buy-and-hold return of the high-minus-low decile portfolios is not significant, the low-beta anomaly on a risk-adjusted basis can be explained by the excessively large dispersion of post-formation betas following adverse beta herding. We also find that the effects of adverse beta herding do not disappear quickly and are persistent over two years. Our results with the Fama-French five-factor model also hold for other estimates of betas from the market model or a ten-factor model.[2]

Contrary to the common belief that herding is significant when the market is in a stressed state (Choe, Kho, and Stulz, 1999; Kim and Wei, 2002), adverse beta herding arises once a crisis appears and uncertainty increases. During market crises, investors become under-confident about the signals they use to predict the market outlook and pessimistic views prevail whereas beta herding becomes more apparent when investors are optimistic or overconfident regarding the future direction of the market.

Our study is distinct from other studies in the literature. First, these effects of beta herding on cross-sectional asset returns differ from those of sentiment. Although sentiment explains returns of portfolios sorted on some firm characteristics (Baker and Wurgler, 2006) and are closely related to betas (Stambaugh, Yu, and Yuan, 2012; Antoniou, Doukas, and Subrahmanyam, 2016), we find that the effects of beta herding on cross-sectional asset returns

[2] Nine firm-characteristics factors in addition to the excess market return are constructed as in the literature, the details of whch are explained in section 4.

are robust in the presence of sentiment. Conversely, beta herding does not explain the firm characteristic-sorted portfolio returns despite the close relationship between betas and the firm characteristics. These results suggest the difference in the mechanism through which beta herding and sentiment affect asset returns. Most studies in the literature investigate asymmetric effects of sentiment and overconfidence on individual assets, in particular, assets with uncertain valuations (e.g., Baker and Wurgler, 2006; Kumar, 2009). Antoniou, Doukas, and Subrahmanyam (2016) recently provide multiple arguments as to why sentiment will most strongly affect high beta stocks, and show that the returns of high-minus-low beta portfolios are negative following high sentiment periods because of the return reversals. On the other hand, we investigate the effects of behavioral biases on asset returns with different perspective in that investors' market-wide overconfidence or sentiment about the direction of the whole market affects cross-sectional asset returns. In particular, adverse beta herding affects individual asset returns because of the excessively large dispersion of betas through investors' pessimism and under-confidence, the effects of which are quite persistent.

Second, the concept of beta herding, i.e., shrinkage in the dispersion of betas, differs from other herd measures proposed in the literature in several respects. We focus directly on deviations from the equilibrium risk-return relation rather than clustering behavior of market experts such as analysts or institutional investors (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999; Sias, 2004; Barber, Odean, and Zhu, 2009; Choi and Sias, 2009; Hirshleifer and Teoh, 2009). These studies do not necessarily tell us whether asset prices themselves are biased due to herding. Simple cross-sectional variability of returns (Christie and Huang, 1995; Chang, Cheng, and Khorana, 2000), as opposed to betas, is not indicative of irrational pricing in the market, as it may just reflect fundamental changes in common factors or factor loadings.

In the next section, we introduce the concept of beta herding and consider the implications for asset pricing. In section 3, we apply this measure to the US equity market. After discussing the empirical properties of the beta herd measure and its robustness to fundamentals are assessed, we then analyze the effects of beta herding in cross-sectional asset pricing in section 4. In section 5, we investigate beta herding with respect to economic events and crises. Finally, we draw some conclusions in section 6.

2. Overconfidence, sentiment, and beta herding

In this section, we propose an aggregate model based on primitive micro models of individual behavioral bias that leads to biases in beta induced by market-wide overconfidence and sentiment.

2.1. Cross-sectional bias in asset pricing driven by overconfidence

We model how the predicted individual asset returns and betas are affected by investors' overconfidence about the information they receive for the prediction of the market return. Let us assume that the excess market return follows $r_{mt+1} = \mu_m + \varepsilon_{mt+1}$, where μ_m is the unconditional market risk premium and ε_{mt+1} is a shock, $\varepsilon_{mt+1} \sim N(0, \sigma^2_{m\varepsilon t+1})$, which is unobservable at time t. The signal informed investors receive for the prediction of the excess market return is noisy: $s_{mt} = \varepsilon_{mt+1} + \epsilon_{mt}$, where ϵ_{mt} is noise, $\epsilon_{mt} \sim N(0, \sigma^2_{m\epsilon t})$, and ε_{mt+1} and ϵ_{mt} are not correlated. For these investors, the state of the world is presented by (r_{mt}, s_{mt}), both of which are independent of each other. In this setting, investors' prediction of r_{mt+1} is decided by their posterior about ε_{mt+1} given s_{mt} whose variance is unknown to investors. Uninformed investors (who do not receive this signal) do not affect asset prices as far as they are not risk-neutral (Daniel, Hirshleifer and Subrahmanyam, 1998).

Suppose that investor overconfidence appears as overprecision in their beliefs about the signal as in Odean (1998), DHS (1998, 2001), Gervais and Odean (2001), and Epstein and Schneider (2008). Upon receiving s_{mt}, informed investors predict the market return with their posterior expectation $E_t^b(r_{mt+1}|s_{mt}) = \mu_m + w_{bt}s_{mt}$, where $w_{bt} = \frac{\sigma_{m\varepsilon t}^2}{\sigma_{m\varepsilon t}^2+\gamma_t\sigma_{m\epsilon t}^2}$ and the super- and sub-scripts b represent behavioral bias, i.e., overprecision. The parameter γ_t in w_{bt} lies between 0 and 1 for overconfident investors who believe that the signal is more precise than it really is. On the other hand, γ_t is larger than 1 if investors are under-confident. If there is no such bias, the weight on the signal is $w_t = \frac{\sigma_{m\varepsilon t}^2}{\sigma_{m\varepsilon t}^2+\sigma_{m\epsilon t}^2}$ with $\gamma_t = 1$.[3]

Lemma 1*: When overconfident (under-confident) investors use their posterior expectation of the market return $E_t^b(r_{mt+1}|s_{mt}) = \mu_m + w_{bt}s_{mt}$ to predict individual asset returns, their posterior expectation of an individual asset return is*

$$E_t(r_{it+1}|E_t^b(r_{mt+1}|s_{mt})) = \beta_{it}^b(\mu_m + w_{bt}s_{mt}) \quad (1)$$

where $\beta_{it}^b = \gamma_t^*\beta_{it}$, $\gamma_t^* = \frac{\sigma_{m\varepsilon t}^2+\gamma_t\sigma_{m\epsilon t}^2}{\sigma_{m\varepsilon t}^2+\sigma_{m\epsilon t}^2}$, $\beta_{it} = \frac{cov_t(\varepsilon_{mt+1},r_{it+1})}{\sigma_{m\varepsilon t}^2}$, *and* $w_{bt} = \frac{\sigma_{m\varepsilon t}^2}{\sigma_{m\varepsilon t}^2+\gamma_t\sigma_{m\epsilon t}^2}$.

Proof: See the Appendix.

For overconfident (under-confident) investors who predict market return is $\mu_m +$

[3] If jointly normally distributed two random variables X and Y have their standard deviations and covariance represented by σ_X^2, σ_Y^2 and σ_{XY}, respectively, the conditional expected value of X given Y is $E(X|Y) = E(X) + \frac{\sigma_{XY}}{\sigma_Y^2}\{Y - E(Y)\}$. See Daniel, Hirshleifer and Subrahmanyam (1998) for the detailed explanation on how the posterior expectation can be affected by overprecision (under-estimation) of σ_Y^2.

$w_{bt}s_{mt}$, β_{it}^{b}s are always downward (upward) biased regardless of the sign of s_{mt} because $1 > \gamma_t^* > w_t$ $(\gamma_t^* > 1)$.[4] The bias factor, γ_t^*, affects both returns and betas in the same way. To see this, we calculate the return difference between individual assets and the market when investors are overconfident about the market outlook and when they are rational Bayesian optimizers. From the results in equation (1), the cross-sectional return difference between asset i and the market is[5]

$$E_t\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt})\right) - E_c\left(E_t\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt})\right)\right) = \gamma_t^*(\beta_{it}-1)(\mu_m + w_{bt}s_{mt}), \quad (2)$$

since $E_c(\beta_{it}^b) = \gamma_t^*$. When investors are rational, i.e., $\gamma_t^* = 1$, the difference is

$$E_t\left(r_{it+1}\middle|E_t(r_{mt+1}|s_{mt})\right) - E_c\left(E_t\left(r_{it+1}\middle|E_t(r_{mt+1}|s_{mt})\right)\right) = (\beta_{it}-1)(\mu_m + w_t s_{mt}). \quad (3)$$

Therefore, the difference between these two cases is $(\beta_{it}-1)(\gamma_t^*-1)\mu_m$ because $w_t = \gamma_t^* w_{bt}$. When investors are overconfident ($1 > \gamma_t^* > w_t$), the expected returns of high and low beta assets are downward and upward biased toward the market return, respectively. On the other hand, when investors are under-confident ($\gamma_t^* > 1$), expected returns are biased away from the expected market return.

This cross-sectional return difference between asset i and the market in equation (2) is driven by the difference in betas between asset i and the market:

$$\beta_{it}^b - E_c(\beta_{it}^b) = \gamma_t^*(\beta_{it} - 1). \quad (4)$$

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[4] Considering the empirical results that most factors proposed in the literature have R-squared values less than 1% for the prediction of the market return (Goyal and Welch, 2008; Kelly and Pruitt, 2013), noise in s_{mt} should be much larger than the shock, and the minimum value of the bias factor in beta, $\frac{\sigma_{m\varepsilon t}^2}{\sigma_{m\varepsilon t}^2+\sigma_{m\epsilon t}^2}$, would be close to zero.

[5] The subscript *c* represents cross-section.

When investors are overconfident ($1 > \gamma_t^* > w_t$), both low betas ($\beta_{it} < 1$) and high betas ($\beta_{it} > 1$) appear closer to the market beta by γ_t^* times, and cross-sectional variance of β_{it}^b, $var_c(\beta_{it}^b) = (\gamma_t^*)^2 var_c(\beta_{it})$, decreases.

Proposition 1: *For overconfident investors who believe that their signals for market are more precise than they really are, individual betas are biased towards the market beta. On the other hand, individual betas are biased away from the market beta when investors are under-confident about their signals for market.*

This result is consistent with the claims of Hwang and Salmon (2004): when investors are overconfident about signals they receive for a factor, the signals are overweighted and the cross-sectional dispersion of its factor loading decreases.

2.2. Cross-sectional bias in asset pricing driven by market sentiment

The effects of sentiment on cross-sectional asset returns have been investigated by many previous studies. While sentiment will affect the entire return distribution, we follow the majority of the literature and define sentiment with reference to its effect on the mean of investors' subjective returns: if it is relatively high (or low), then an optimistic (or pessimistic) sentiment exists.

When a strong market-wide sentiment prevails such that a similar level of sentiment is observed for individual assets regardless of their equilibrium relation, unsophisticated investors herd to the market-wide sentiment, disregarding fundamentals.[6] To model the effects of the

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[6] The studies such as Baker and Wurgler (2006), Kumar (2009), Stambaugh, Yu, and Yuan (2012), and Antoniou,

market-wide sentiment on cross-sectional asset returns, suppose δ_t denote the impact of sentiment on beliefs regarding the expected returns of all assets in the market. Then, the unsophisticated investors' biased expectation in the presence of sentiment can be found as the sum of two components, one due to fundamentals and the other due to sentiment,

$$E_t^b(r_{it+1}) = E_t(r_{it+1}) + \delta_t, \tag{5}$$

$$E_t^b(r_{mt+1}) = E_t(r_{mt+1}) + \delta_t.$$

As in the previous case, rational and sophisticated investors do not affect asset prices under the assumption that they are not risk-neutral. Then the effects of sentiment on beta can be analyzed using the following equation:

$$\beta_{it}^b = \frac{E_t^b(r_{it+1})}{E_t^b(r_{mt+1})} = \frac{\beta_{it}+\delta_t^*}{1+\delta_t^*}, \tag{6}$$

where β_{it}^b is the systematic risk in the presence of sentiment, and $\delta_t^* = \frac{\delta_t}{E_t(r_{mt+1})}$ represents sentiments relative to the expected excess market return.

There is no change in the cross-sectional return difference, i.e., $E_t^b(r_{it+1}) - E_t^b(r_{mt+1}) = E_t(r_{it+1}) - E_t(r_{mt+1})$, because all individual asset returns would move by the same value. However, the cross-sectional deviation in betas from the market beta becomes

$$\beta_{it}^b - E_c(\beta_{it}^b) = \frac{1}{1+\delta_t^*}(\beta_{it} - 1), \tag{7}$$

Doukas, and Subrahmanyam (2016) investigate the case that individual assets respond sensitively to sentiment or overconfidence if these assets are difficult to value or arbitrage. This can be modelled by assuming positive correlation between δ_{it} and β_{it} during high (low) sentiment periods in our framework. Then, high (low) beta stocks appear to outperform low (high) beta stocks, but this outperformance reverses subsequently. In our study, however, we investigate the effects of market-wide sentiment by assuming $\delta_{mt}^* = \delta_{it}^*$ for all individual assets.

since $E_c(\beta_{it}^b) = 1$. Equation (7) shows that as market-wide sentiment δ_t^* increases (optimistic sentiment), individual betas are biased towards the market beta: $1 > \beta_{it}^b > \beta_{it}$ for assets with $\beta_{it} < 1$ and $1 < \beta_{it}^b < \beta_{it}$ for $\beta_{it} > 1$. Similarly, when δ_t^* is negative (pessimistic sentiment), $1 < \beta_{it} < \beta_{it}^b$ for assets with $\beta_{it} > 1$ and $1 > \beta_{it} > \beta_{it}^b$ for assets with $\beta_{it} < 1$. Therefore, when asset pricing based on fundamentals is suppressed by sentiment, then the dispersion of individual betas shrinks or increases with optimistic or pessimistic sentiment, respectively, although cross-sectional return difference remains unchanged. We thus have the following proposition.

Proposition 2: *When a strong positive (negative) sentiment prevails such that a similar level of sentiment is anticipated for individual assets regardless of their equilibrium risk-return relation, individual betas are biased towards (away from) the market beta.*

2.3. Beta herding

Although the driving forces behind investor overconfidence and sentiment are different, they have a common effect on betas through a biased probability distribution in expected returns. When this form of biased expectation exists among investors, they will follow the performance of the market portfolio when buying or selling assets, and thereby betas are biased towards the market beta. We define such shrinkage in betas as *beta herding*.

Definition *Beta herding represents the cross-sectional bias in betas that herd towards the market beta.*

The bias in beta by investor overconfidence regarding the market outlook can be analyzed together with that by market-wide sentiment. As in the above, suppose that investors are overconfident about the market outlook and that a strong market-wide investor sentiment prevails regardless of individual assets. For simplicity, assume that sentiment is not related to overconfidence and is additive to the posterior expectation. Then, investors' posterior expectation for the prediction of the market return is:

$$E_t^b(r_{mt+1}|s_{mt}, \delta_t) = (\mu_m + w_{bt}s_{mt}) + \delta_t,$$

and individual asset returns conditional on this market outlook are predicted as follows:

$$E_t^b\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt}, \delta_t)\right) = \gamma_t^*\beta_{it}(\mu_m + w_{bt}s_{mt}) + \delta_t.$$

Lemma 2*: When sentiment is not related to overconfidence and is additive to the posterior expectation, the cross-sectional return difference between asset* i *and the market is*

$$E_t^b\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt}, \delta_t)\right) - E_c\left(E_t^b\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt}, \delta_t)\right)\right)$$
$$= \gamma_t^*(\beta_{it} - 1)(\mu_m + w_{bt}s_{mt}), \quad (8)$$

and the difference in betas between individual assets and the market is

$$\beta_{it}^b - E_c(\beta_{it}^b) = \frac{\gamma_t^*}{1+\delta_t^{**}}(\beta_{it} - 1). \quad (9)$$

where $\delta_t^{**} = \frac{\delta_t}{(\mu_m + w_{bt}s_{mt})}$ is the market-wide investor sentiment with respect to the predicted market return and $\gamma_t^* = \frac{\sigma_{m\varepsilon t}^2 + \gamma_t\sigma_{m\epsilon t}^2}{\sigma_{m\varepsilon t}^2 + \sigma_{m\epsilon t}^2}$ represents overconfidence when $1 > \gamma_t^*$.

Proof: See the Appendix.

The component, δ_t^{**}, captures the effects of the market-wide sentiment on betas in a similar way to equation (7): when investor's optimism increases, the difference between individual betas and the market beta decreases. On the other hand, γ_t^* measures the overconfidence driven beta herding as in (4): betas converge to the market beta as γ_t^* decreases. We summarize four cases in Table 1 to show how γ_t^* and δ_t^{**} affect beta herding. When $\delta_t^{**} \rightarrow \infty$ or $\gamma_t^* \rightarrow 0$, $\beta_{it}^b \rightarrow E_c(\beta_{it}^b)$ for all i and the expected excess returns on the individual assets will approach the market return regardless of their systematic risks. Thus, this case can be interpreted as 'perfect' beta herding. In general, when $\delta_t^{**} > 0$ or $0 < \gamma_t^* < 1$, beta herding exists in the market, and the size of the bias will depend on the magnitude of δ_t^{**} or γ_t^*: $|\beta_{it}^b - E_c(\beta_{it}^b)| < |\beta_{it} - 1|$. When $\delta_t^{**} < 0$ or $\gamma_t^* > 1$, adverse beta herding arises. In this case a low beta asset will be less sensitive to movements in the market portfolio whereas a high beta asset will be more sensitive to movements in the market portfolio: $|\beta_{it}^b - E_c(\beta_{it}^b)| > |\beta_{it} - 1|$.

2.4. A measure of beta herding

In order to measure beta herding, we calculate the cross-sectional variance of betas that varies depending on γ_t^* or δ_t^{**}. Using equation (9), we have the following relation between $Var_c(\beta_{it}^b)$ and the two parameters that contribute to beta herding (i.e., γ_t^* and δ_t^{**}):

$$Var_c(\beta_{it}^b) = \left(\frac{\gamma_t^*}{1+\delta_t^{**}}\right)^2 Var_c(\beta_{it}) \quad (10)$$

where $Var_c(.)$ represents cross-sectional variance. For given $Var_c(\beta_{it})$, the dynamics of $Var_c(\beta_{it}^b)$ reflect changes in irrational pricing due to sentiment (δ_t^{**}) or overconfidence (γ_t^*): as δ_t^{**} increases or γ_t^* decreases, $\left(\frac{\gamma_t^*}{1+\delta_t^{**}}\right)^2$ decreases and beta herding intensifies.

We propose $Var_c(\beta_{it}^b)$ as a measure of beta herding, which we denote by H_t. As beta herding represents cross-sectional bias in beta, it is important to control the effects of

$Var_c(\beta_{it})$. It is well documented that betas do change over time (Ferson and Harvey, 1991, 1995; Jagannathan and Wang, 1996; Lewellen and Nagel, 2006; Ang and Chen, 2006). However, in the literature, little is known about the dynamics of the cross-sectional variance of betas. In this study, we control the dynamics of $Var_c(\beta_{it})$ using various variables proposed to explain betas and other cross-sectional return patterns. Our results, details of which will be explained later, show that $Var_c(\beta_{it}^b)$ is not explained by these variables.

An obvious obstacle in calculating the beta herd measure (H_t) is that β_{it}^b is unknown and needs to be estimated. Using the popular least squares (LS) estimate of β_{it}^b, i.e., $\hat{\beta}_{it}^b$, we may calculate the beta herd measure as follows:

$$H_t^O = \frac{1}{\mathrm{N}-1}\sum_{i=1}^{\mathrm{N}} \left(\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}\right)^2, \tag{11}$$

which can be decomposed as follows:

$$H_t^O = \frac{1}{\mathrm{N}-1}\sum_{i=1}^{\mathrm{N}} (\beta_{it}^b - \overline{\hat{\beta}_{it}^b})^2 + \frac{1}{\mathrm{N}-1}\sum_{i=1}^{\mathrm{N}} \eta_{it}^2, \tag{12}$$

using $\hat{\beta}_{it}^b = \beta_{it}^b + \eta_{it}$, where η_{it} is the estimation error. Only when $\frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}} \eta_{it}^2$ (the cross-sectional variance of estimation errors, CVEE) is constant, then the dynamics of H_t can be captured by H_t^O. However, the estimation errors are heteroskedastic because of the heteroscedasticity of idiosyncratic errors and market returns (Campbell, Lettau, Malkiel, and Xu, 2001). The dynamics of H_t^O are not likely to arise from changes in beta herding, but originate from heteroskedastic behavior in the CVEE.

Our approach to avoid this unpleasant property of H_t^O is to standardize $\hat{\beta}_{it}^b$ with its standard error (Bring, 1994): in other words, we use the t statistic of $\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}$ instead of $\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}$. Our measure of beta herding is calculated as

$$H_t^* = \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \left(\frac{\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}}{\hat{\sigma}_{\hat{\beta}_{it}^b}} \right)^2, \quad (13)$$

where $\hat{\sigma}_{\hat{\beta}_{it}^b}$ is the standard error of $\hat{\beta}_{it}^b$. Henceforth, we refer to H_t^O in expression (11) as the beta-based herd measure, whereas $\frac{\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}}{\hat{\sigma}_{\hat{\beta}_{it}^b}}$ and H_t^* in (13) are referred to as standardized-beta and the standardized-beta herd measure, respectively. Note that a lower value of H_t^* (H_t^O) indicates higher beta herding.

There are several benefits of using standardized-beta, $\frac{\beta_{it}^b - \mathrm{E}(\beta_{it}^b)}{\sigma_{\beta_{it}^b}}$. First, it becomes possible to compare the dynamics of beta herding over different periods. The standardized-beta has a homoscedastic distribution and thus will not be affected by any heteroskedastic behavior in estimation errors. When estimation error $\eta_{it} \sim (0, \sigma_{\beta_{it}^b}^2)$ is standardized with its own standard deviation, we have $\frac{\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}}{\sigma_{\beta_{it}^b}} = \frac{\beta_{it}^b - \overline{\hat{\beta}_{it}^b}}{\sigma_{\beta_{it}^b}} + \eta_{it}^*$ from $\hat{\beta}_{it}^b = \beta_{it}^b + \eta_{it}$, where $\eta_{it}^* \sim (0,1)$ for all *i* and *t*. Therefore, as the number of stocks increases, $\lim_{\mathrm{N}\to\infty} \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \left(\frac{\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}}{\hat{\sigma}_{\hat{\beta}_{it}^b}} \right)^2 = \lim_{\mathrm{N}\to\infty} \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \left(\frac{\beta_{it}^b - \mathrm{E}(\beta_{it}^b)}{\sigma_{\beta_{it}^b}} \right)^2 + 1$ is not affected by estimation error. Second, the *t* statistic provides information on the precision of the beta estimate in addition to the magnitude of the beta estimate. The reciprocal of estimation error in the denominator of the *t* statistic represents precision whereas the numerator of the *t* statistic shows how much a beta is deviated from the market beta. Thus, the standardized-beta should be informative in asset pricing. Third, this herd measure, H_t^*, can be easily calculated using standard estimation programs, as it is based on the cross-sectional variance of the t statistics of the estimated coefficients on the market portfolio.

Alternatively, the beta-based herd measure can be used for portfolios because the estimation error can be minimized as the number of equities within each portfolio increases (Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973): for a portfolio p with equal weights, we have $p\lim\hat{\beta}_{pt}^{b} = \beta_{pt}^{b}$ because $\hat{\beta}_{pt}^{b} = \frac{1}{N_p}\sum_{i=1}^{N_p}\hat{\beta}_{it}^{b} = \frac{1}{N_p}\sum_{i=1}^{N_p}\beta_{it}^{b} + \frac{1}{N_p}\sum_{i=1}^{N_p}\eta_{it}$, where N_p is the number of stocks in the portfolio. In the empirical tests, we show that the beta-based herd measures calculated with portfolios are indeed similar to the standardized-beta herd measure calculated with individual stocks.

The following distributional result applies to (13).[7]

Theorem 1 *Let* $\widehat{\boldsymbol{\beta}}^{*} = (\hat{\beta}_1^{*} \quad \hat{\beta}_2^{*} \quad . \quad \hat{\beta}_N^{*})'$, *where* $\hat{\beta}_i^{*} = \frac{\hat{\beta}_{it}^{b} - \overline{\hat{\beta}_{it}^{b}}}{\hat{\sigma}_{\hat{\beta}_{it}^{b}}}$ *and* $\hat{\sigma}_{\hat{\beta}_i^{b}}$ *is the standard error of* $\hat{\beta}_i^{b}$. *Then with the classical LS assumptions,*

$$\underset{N\times 1}{\widehat{\boldsymbol{\beta}}^{*}} \sim N\left(\underset{N\times 1}{\boldsymbol{\beta}^{*}}, \underset{N\times N}{\boldsymbol{V}^{*}}\right),$$

where $\boldsymbol{\beta}^{*} = (\beta_1^{*} \quad \beta_2^{*} \quad . \quad \beta_N^{*})'$, $\beta_i^{*} = \frac{\beta_i^{b} - E(\beta_i^{b})}{\sigma_{\beta_i^{b}}}$, *and* $\boldsymbol{V}^{*}$ *is covariance matrix of* $\widehat{\boldsymbol{\beta}}^{*}$. *Then*

$$H^{*} = \frac{1}{N}\widehat{\boldsymbol{\beta}}^{*\prime}\widehat{\boldsymbol{\beta}}^{*} \sim \frac{1}{N}[\chi^2(R; \beta^{*R}) + c^{*}], \qquad (14)$$

where R *is the rank of* $\boldsymbol{V}^{*}$, $\beta^{*R} = \sum_{j=1}^{R}(\beta_j^{A*})^2/\lambda_j^{*}$, $c^{*} = \sum_{j=R+1}^{N}(\beta_j^{A*})^2$, β_j^{A*} *is the* j*th element of the vector* $\boldsymbol{C}^{*\prime}\widehat{\boldsymbol{\beta}}^{*}$, *and* $\boldsymbol{C}^{*}$ *and* $\boldsymbol{\Lambda}^{*}$ *are the* $(N \times N)$ *matrices of the eigenvectors and eigenvalues of* $\boldsymbol{V}^{*}$, *respectively, i.e.,* $\boldsymbol{V}^{*} = \boldsymbol{C}^{*}\boldsymbol{\Lambda}^{*}\boldsymbol{C}^{*\prime}$. λ_j^{*} *is the jth eigenvalue of the diagonal matrix* $\boldsymbol{\Lambda}^{*}$. *The eigenvalues are sorted in descending order.*

Proof. See the Appendix.

[7] The notation for beta and other parameters is simplified in the theorem by omitting the subscript *t*.

Theorem 1 shows that the measure of beta herding is distributed as $1/N$ times the sum of non-central χ^2 distributions with degrees of freedom R with non-centrality parameter β^{*R} and a constant. Therefore, the variance of H_t^* is given by

$$Var[H_t^*] = \frac{2}{N^2}[R + 2\beta^{*R}]. \quad (15)$$

In practice, the non-centrality parameter would be replaced with its sample estimate. It is worth noting that this distributional result depends on the assumption that the number of observations used to estimate β_{it}^b is sufficiently large and $\hat{\boldsymbol{\beta}}_t^*$ is multivariate normal. With too few observations, the confidence level implied in the theorem above would be smaller than it would be asymptotically and we would thus reject the null hypothesis too frequently.

3. Empirical properties of beta herding

3.1. Estimation of beta herding

Betas are estimated using rolling windows of τ (minimum 24) monthly observations and the beta herd measure and its confidence interval are updated as shown in Theorem 1.[8] Following the literature (e.g., Fama and French, 1992; Baker, Bradley, and Taliaferro, 2014), we set $\tau = 60$ months to estimate standardized-betas and H_t^*. Betas and standardized-betas are estimated in the presence of Fama-French factors, size (Small-minus-Big, SMB), book-to-

[8] Conditional models similar to those of Jagannathan and Wang (1996), Ferson and Harvey (1999), or Ang and Chen (2006) could be used. However, these models may be over-parameterized (Fama and French, 2006), or as demonstrated by Ghysels (1998), Jostova and Philipov (2005), and Lewellen and Nagel (2006), they do not necessarily specify beta better than simple linear models unless the true process is known. Moreover, the cost of using the conditional models for tens of thousands of stocks would be prohibitively high.

market (High-minus-Low, HML), profitability (Robust-minus-Weak profitability, RMW), and investment (Conservative-minus-Aggressive investment, CMA) (Fama and French, 2015). For robustness, we also test various other windows, i.e., τ =48 and 84 months. Other models, i.e., the market model and a ten-factor model, are also tested. The details of the results are reported later. The bottom line is that our main story does not change significantly.

The monthly data file comes from the merged Center for Research in Security Prices (CRSP) – Compustat database for common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. Using rolling windows of τ months we obtain 600 monthly beta-based and standardized-beta herding statistics (H_t^O and H_t^*) from January 1967 to December 2016. The number of stocks starts with 940 at January 1967 and increases to 2,800 at December 2015. The maximum number of stocks is 3,580 at December 1996. For excess market returns, the CRSP value weighted market portfolio returns and 1-month treasury bills are used.

Heard measures are also estimated using portfolios to investigate robustness of the standardized-beta herd measure we estimate with individual stocks. The portfolios we use include the Fama-French 50 portfolios formed on firm characteristics (25 portfolios formed on size and book-to-market and 25 portfolios formed on operating profitability and investment), 100 portfolios formed on size and book-to-market, and 49 industry portfolios from Kenneth French's data library. Industries that include less than five firms at the time of estimation are omitted.

3.2. Empirical properties of beta herd measures

Table 2 reports some of the basic statistical properties of the beta-based and standardized-beta herding statistics, with the market model and the Fama-French five-factor model. All beta herd measures are highly non-normal being positively skewed and leptokurtic.

The beta-based measures (H_t^O) from the market model and the five-factor model (the first two columns in Table 2) are close to each other: the rank correlation coefficient between the two is 0.96. The beta-based measure is not affected in a meaningful way by the inclusion of the four factors. However, the last two columns of Table 2 show some difference in H_t^* between the market model and the five-factor model: the rank correlation coefficient between the two is only 0.53. The high correlation in H_t^O and the relatively lower correlation in H_t^* indicate that the standard errors of the estimated betas are affected by the additional four factors.

The last row in Table 2 reports a significant difference between H_t^O and H_t^*; the rank correlations between the two are negatively correlated, i.e., -0.15, for the five-factor model. In order to investigate if the difference comes from estimation errors as explained in equation (12), the beta-based herd measure is regressed on the standardized-beta herd measure with and without CVEE:

$$H_t^O = \underset{(0.053)}{0.402} - \underset{(0.021)}{0.031} H_t^* + e_t,$$

$$H_t^O = \underset{(0.019)}{-0.146} + \underset{(0.031)}{1.193} CVEE_t + \underset{(0.007)}{0.077} H_t^* + e_t,$$

where the numbers in the brackets are Newey-West standard errors, and $CVEE_t$ is calculated by taking the cross-sectional average value of the squared standard errors of $\hat{\beta}_{it}^b$s. The adjusted R^2 value of the regression is 0.01 and 0.95 for the first and second regressions, respectively. These results clearly indicate that the dynamics of H_t^O are driven by CVEE as in equation (12). Once CVEE is taken out, a strong positive relation between the two beta herd measures emerges.

3.3. Robustness to fundamentals and estimation errors

An issue, as discussed at the outset, is whether the dynamics of the beta herding statistics are driven by either fundamentals or estimation errors. The two beta herd measures (H_t^O and H_t^*) are regressed on various variables frequently used to explain beta or to control the effects of fundamentals on behavioral biases (Ferson and Harvey, 1991, 1999; Baker an Wurgler, 2006). The variables are one-month Treasury bill rate (TB_t), the term spread (TS_t, the difference between the US ten year and one year Treasury bond rate), the credit spread (CS_t, the difference between Moody's Aaa and Baa rated corporate bonds), the dividend yield (DY_t, the dividend yield of S&P500 index), the Lettau and Ludvigson (2001) consumption-wealth ratio (CAY_t), the monthly inflation rate (CPI_t), the growth in industrial production (IP_t), the growth in consumption of durables, nondurables, and services ($Cons_t$), the unemployment rate ($Unemp_t$), and a dummy variable for NBER recessions ($NBER_t$).[9] We also add market returns and market volatility to investigate whether or not our beta herd measures depend on different market conditions. Market volatility is calculated by summing squared daily returns as in Schwert (1989). A lagged beta herd statistic is included as an explanatory variable to control for the persistence of the measure.

The results are reported in Table 3. Beta herd measures appear highly persistent but are stationary.[10] In addition to the persistence of beta, the rolling windows we use to estimate betas

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[9] These data are obtained from the Federal Reserve Bank of St. Louis.

[10] The augmented Dickey-Fuller test rejects the null hypothesis of a unit root at 5% significance level. The persistence of the measures is not surprising since betas are well-known to be highly persistent both theoretically as well as empirically: for example, Gomes, Kogan, and Zhang (2003) and Ang and Chen (2006) suggest

also contribute to the persistence of H_t^*.

Controlling for the persistence of the measure, we find little evidence that H_t^* is affected by the macroeconomic variables (Panel B of Table 3). Therefore, despite the evidence that betas change in response to lagged macroeconomic variables (Jagannathan and Wang, 1996; Ferson and Harvey, 1999), the cross-sectional variance of standardized-betas does not.[11] This result could be interpreted as showing that changes in economic conditions increase some betas while decreasing others, leaving the level of cross-sectional dispersion little changed.

As expected, the coefficients on $CVEE_t$ are positive and significant for the beta-based measure. More importantly, the thin solid and dotted lines at the bottom of Figure 1 confirm that the dynamics of the beta-based herd measure are dominated by the estimation error: the rank correlation coefficient between H_t^O and $CVEE_t$ is 0.96. On the other hand, H_t^* appears to be negatively affected by CVEE. As H_t^* is robust to estimation error (subsection 2.4), we evaluate the importance of CVEE on H_t^* by calculating an orthogonalized standardized-beta herd measure ($H_t^{*\perp}$) free from CVEE, the two market variables, and the ten macroeconomic fundamentals using the regression results in the last row of Table 3. Figure 1 demonstrates that the dynamics of H_t^* and $H_t^{*\perp}$ are not different from each other: the rank correlation coefficient between H_t^* and $H_t^{*\perp}$ is 0.99. These results are consistent with the marginal contribution (i.e., little difference in the adjusted R-square value) of the control variables to the

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autoregressive coefficients larger than 0.95 for monthly data.

[11] Our empirical results rule out that possibility that the standardized herd measure may be affected by a sudden change in the leverage during crises. According to Korteweg (2010), firms do not adjust their leverage ratios even if their current leverage ratios are suboptimal, and thus leverage ratios are quite stable over time.

model with persistence.

Between the two market variables, market return does not explain H_t^*. The impact of investor overconfidence or sentiment on beta herding can occur whether the market is moving up or down. Market volatility, on the other hand, does have a positive relation with H_t^*, suggesting that adverse beta herding arises when market volatility increases. We return to this relation later.

The bottom line is that the dynamics of H_t^* can be interpreted as changes in behavioral forces driven by investor sentiment or overconfidence towards the market outlook.[12] In the following analysis we report our results using H_t^*, as we find that the results with $H_t^{*\perp}$ are effectively the same as those with H_t^*.

4. The effects of beta herding on cross-sectional asset returns

When the dispersion of standardized-betas changes dramatically over time as in Figure 1, the cross-sectional return difference between high and low standardized-beta stocks would not remain constant. In this section, we scrutinize the effects of beta herding on cross-sectional asset returns.

[12] The dynamics of the cross-sectional dispersion of standardized-betas is not driven by a small number of stocks whose extremely high or low betas change dramatically. When decile portfolios are formed on the standardized-betas, both positive and negative standardized-betas move in mirror image, indicating that H_t^* is driven by the entire beta distribution.

4.1. Cross-sectional asset returns conditional on beta herding

We first investigate if portfolios formed on standardized-betas show difference in their performance depending on the level of beta herding. The sample period is divided into three sub-periods depending on the level of H_t^* at the formation month and then the post-formation performance of standardized-beta portfolios for each of these herding states is compared: i.e., beta herding (the bottom 20% of H_t^*), no beta herding (middle 60% of H_t^*), and adverse beta herding (top 20% of H_t^*). Decile portfolios are formed on standardized-betas estimated using the Fama-French five-factor model. For each of the decile portfolios, risk adjusted buy-and-hold returns over 12 months from the formation are calculated using the five-factor model.

None of the buy-and-hold returns of the high-minus-low portfolios in Table 4 is significant, confirming the empirical results in the literature (e.g., Fama and French, 1992). However, the low-beta anomaly that low beta stocks outperform high beta stocks on a risk-adjusted basis (Baker, Bradley, and Wurgler, 2011; Baker, Bradley, and Taliaferro, 2014) still holds for the standardized-beta portfolios: the risk-adjusted returns of the high-minus-low beta portfolios are negative and significant: -5.97% and -8.7% for equally- and value-weighted portfolios, respectively. Even though standardized-betas are used instead of betas in the five-factor model, the empirical results are consistent with those reported in the literature.[13]

According to this inverse relation between beta and risk-adjusted return, it should be adverse beta herding that contributes to the negative risk-adjusted return of the high-minus-low

[13] For the explanations of the low-beta anomaly, see lottery-like risk (Bali, Cakici, and Whitelaw, 2011), leverage (Frazzini and Pedersen, 2014), speculative motives to trade (Hong and Sraer, 2016), or downside risk (Schneider, Wagner, and Zechner, 2016).

beta portfolio rather than beta herding. The low-beta anomaly should increase when the difference between high and low betas increases if the low-beta anomaly is driven by the inverse relation between beta and risk-adjusted return. The results in Table 4 report that the negative risk-adjusted returns of the high-minus-low standardized-beta portfolios increase following adverse beta herding, ranging from -17.12% (equal-weights) to -12.32% (value-weights), and are significant at 5% level. The low-beta anomaly becomes stronger following adverse beta herding.

The increase in the low-beta anomaly following adverse beta herding can be explained by a large difference in post-formation betas. Despite the insignificant difference in the post-formation raw returns between high and low standardized-beta sorted portfolios, the difference in the post-formation betas are 0.95 (equal-weights) and 0.64 (value-weights) following adverse beta herding, whereas they are only 0.27 (equal-weights) and 0.47 (value-weights) following beta herding. These differences are significant at the 5% level, and thus the difference in the post-formation betas changes significantly depending on the level of beta herding, affecting risk-adjusted returns.[14]

These results indicate that the low-beta anomaly arises when the dispersion of betas increases excessively due to investors' under-confidence or pessimistic views about market

[14] The low-beta anomaly following beta herding also appears to be large. Despite the small difference in betas between high and low standardized-beta portfolios following beta herding, e.g., 0.27 for equally weighted portfolios, the risk-adjusted returns of the high-minus-low standardized-beta portfolios are large and negative, ranging from -8.62% (value-weights) to -4.52% (equal-weights). However, the negative risk-adjusted returns following beta herding are not robust for other estimates of betas and there is little evidence of return difference between beta-herding and adverse-beta herding (Tables 5 and 8).

outlook. When investors have little confidence about the signals they use for the prediction of market movements (a large value of γ_t^*) or have pessimistic views (a negative value of δ_{mt}^{**}), individual betas are biased so that the difference between individual betas increases.

4.2. Persistence and asymmetric responses

The performance of the standardized-beta portfolios is further investigated for different forecasting horizons and for asymmetric responses to beta herding. The post-formation returns of the high-minus-low standardized-beta quintile portfolio are regressed on the lagged H_t^* in the presence of other control variables:

$$r_{High,t+f}^{\beta} - r_{Low,t+f}^{\beta} = \alpha + c_1 H_t^* + \sum_{k=2}^{K} c_k f_{k,t+f} + \varepsilon_{i,t+f},$$

$$r_{High,t+f}^{\beta} - r_{Low,t+f}^{\beta} = \alpha + c_1^+ H_t^* I_t + c_1^- H_t^* (1 - I_t) + \sum_{k=2}^{K} c_k f_{k,t+f} + \varepsilon_{i,t+f},$$

where the forecasting horizon is set to f=3, 9, …, 36, and $I_{\mathrm{t}} = 1$ if $H_t^* > \frac{1}{T}\sum_{t=1}^{T} H_t^*$ and $I_{\mathrm{t}} = 0$ otherwise. As in Jegadeesh and Titman (2001), overlapping portfolios are constructed to increase the power of the tests. For instance, the post-formation return of the high standardized-beta portfolio $r_{High,t+f}^{\beta}$ is calculated by equally weighting f high standardized-beta portfolios formed at t, $t+1$, ..., $t+f-1$. Fama-French five factors are used as the control variables. Asymmetric responses to beta herding and adverse beta herding can be tested by the difference between c_1^+ and c_1^-.

The results in Table 5 confirm that beta herding matters in cross-sectional asset returns. The negative coefficients on H_t^* suggest that when adverse beta herding arises, i.e., H_t^* increases, subsequent high-minus-low standardized-beta portfolio returns decrease. For the forecasting horizons from 3 months to 36 months, all coefficients on H_t^* are negative and some of them are significant at the 5% level. When the herd measure is divided into adverse beta herding and beta herding states, both coefficients c_1^+ and c_1^- are negative and there is little statistical evidence of difference between them. The results with value-weights are not inconsistent with those with equal-weights but are weaker than those with equal-weights, indicating that small stocks are affected by beta herding.

When beta herding is considered, the low-beta anomaly disappears because of the negative coefficients on H_t^*. The results in Table 5 show that without considering beta herding, risk-adjusted returns of high-minus-low standardized-beta portfolios are negative and significant as in Baker, Bradley, and Wurgler (2011) and Baker, Bradley, and Taliaferro (2014). However, when beta herding is considered, the risk-adjusted high-minus-low standardized-beta portfolio return becomes positive but not significant. These results together with the -17.12% of risk-adjusted returns following adverse beta herding (Table 4) indicate that the low-beta anomaly arises due to the excessively large dispersion of betas.

The effects of beta herding on beta sorted portfolio returns appear quite persistent. For example, the coefficients are large when H_t^* is lagged by 12 to 30 months, and are significant for the 30 month lagged herd measure for the equally weighted portfolios in panel A of Table 5. The persistence reflects the difficulty that investors face when they estimate the true betas. Even with more information, the effects of adverse herding on asset returns do not disappear because betas in practice are at best estimates with large estimation errors (Damodaran, 2012).

4.3. The Effects of beta herding and sentiment on cross-sectional asset returns

Our model suggests that beta herding increases with sentiment. Using Baker and

Wurgler (2006) sentiment index (BW), we find that the correlation coefficient between H_t^* and the BW sentiment index is negative and significant, i.e., -0.38. Therefore, as predicted in Lemma 2, beta herding increases with sentiment.

However, the negative correlation between H_t^* and the BW sentiment index suggests that our study on the effects of investor overconfidence and sentiment about the market outlook are different from those that associate overconfidence and sentiment with assets with uncertain valuations (e.g., Baker and Wurgler, 2006; Kumar, 2009). According to Antoniou, Doukas, and Subrahmanyam (2016), high beta stocks are more likely to be affected by investor optimism than low beta stocks are, and the inverse relationship between risk and return following optimism reflects the subsequent return reversals. If the effects of beta herding echo those of sentiment, then returns of high-minus-low standardized-beta portfolios should have positive coefficients on the lagged H_t^* because of the negative correlation between sentiment and H_t^*.

We investigate this by regressing the post-formation returns of the high-minus-low standardized-beta quintile portfolio on the lagged H_t^* and BW sentiment index in the presence of other control variables:

$$r_{High,t+f}^{\beta} - r_{Low,t+f}^{\beta} = \alpha + c_1 H_t^* + c_2 S_t^* + \sum_{k=3}^{K} c_{\mathrm{k}} f_{k,t+f} + \varepsilon_{i,t+f},$$

where the forecasting horizon is set to f=3, 12, …, 36, and S_t^* is the Baker and Wurgler sentiment index. Fama-French five-factors and ten-factors are used as control variables.[15]

[15] The nine factors in addition to the excess market return include six annually rebalanced portfolios formed on annual accounting variables and three monthly rebalanced portfolios formed on quarterly accounting variables or monthly market information. Six annually rebalanced portfolios include accruals (Sloan, 1996); asset growth

Table 6 shows that the effects of beta herding becomes more clear than those in Table 5. Most coefficients on H_t^* are negative and significant at the 5% level, supporting that the low-beta anomaly increases with investors' under-confidence and pessimism about the entire market. We also find that the coefficients on the lagged sentiment index is negative too. As in Antoniou, Doukas, and Subrahmanyam (2016), if unsophisticated investors' optimism increases returns of high beta stocks than those of low beta stocks, high beta stocks underperform low beta stocks following investors' optimism because of the return reversals. These results, however, disappear when portfolios are value-weighted.

The negative correlation between sentiment and H_t^* and the robustness of the coefficients on the lagged H_t^* in Table 6 show that the effects of beta herding on asset returns differ from those of sentiment. In our model, sentiment and overconfidence are not assumed to vary at the cross-sectional level, but instead cross-sectional effects arise indirectly through the effects of investors' sentiment and overconfidence about the entire market outlook. On the

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(Cooper, Gulen, and Schill, 2008); book-to-market ratio (Rosenberg, Reid, and Lanstein, 1985; Fama and French, 1992, 1993); gross profitability (Novy-Marx, 2010); net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004); and net stocks issues (Fama and French, 2008). The three monthly rebalanced portfolios are size (Banz, 1980; Fama and French, 1992, 1993); momentum (Jegadeesh and Titman, 1993, 2001); and earnings surprises (Chan, Jegadeesh, and Lakonishok, 1996). Ten equally weighted portfolios are formed for each trading strategy, and then a hedge portfolio is obtained by the difference between the highest and the lowest decile portfolios. Detailed explanations can be obtained from the authors upon request. We have also considered various other factors suggested in the literature (Harvey, Liu, and Zhu, 2014), but these are highly correlated with the ten factors we use in this study (correlation coefficients are larger than 0.7) or are not significant for the explanation of asset returns in our sample. the nine our factors may appear small.

other hand, Antoniou, Doukas, and Subrahmanyam (2016) take the view that sentiment or overconfidence has asymmetric effects on assets with uncertain valuations (e.g., Baker and Wurgler, 2006; Kumar, 2009). Our results show that these two effects co-exist in the market: both market-wide sentiment and overconfidence directly or indirectly affects cross-sectional asset returns. These, however, have the opposite consequences.

4.4. Beta herding and firm characteristics

If beta is closely correlated with other firm characteristics, then the performance of portfolios formed on standardized-betas may be affected by firm characteristics or the performance of portfolio formed on firm characteristics may be affected by beta herding. In panel B of Table 6 (and also panel B of Table 8), we have already showed that high-minus-low standardized-beta portfolio returns negatively depend on lagged H_t^* after controlling nine other firm characteristic factors. Therefore, firm characteristics do not subsume the conditional effects of beta herding on the performance of standardized-beta sorted portfolios. In this subsection, we investigate the effects of beta herding on the portfolios formed on the firm characteristics.

Table 7 shows that firm characteristics are strongly correlated with the standardized-betas.[16] The standardized-betas increase with betas, suggesting that the information contained in betas is not undermined by the standardization. High standardized-beta stocks are less likely to pay dividends, have less tangible assets, but are more likely to rely on external finance, and show higher sales growth and idiosyncratic volatility. They also show higher profits and past

[16] The firm characteristics are calculated as in Baker and Wurgler (2006), Amihud (2002), and Ang et. al. (2006).

returns, and are liquid. However, they are neither small nor distressed (i.e., high book-to-market). Contrary to the results of Fama and French (1992) who demonstrate that high beta stocks tend to be smaller than low beta stocks, high standardized-beta stocks are larger than low standardized-beta stocks.[17]

The performance of portfolios formed on these firm characteristics is investigated by regressing high-minus-low portfolio returns ($r_{High,t+f} - r_{Low,t+f}$) formed on firm characteristics on the lagged beta herd measure and sentiment as in Baker and Wurgler (2006). The results (not reported) show that beta herding does not predict the performance of the firm characteristics-sorted portfolios although the relation between standardized-beta and firm characteristics is strong. Some effects of sentiment on the performance of these firm characteristics disappear in the presence of the Fama-French five factors, because the two additional factors, i.e., profitability and investment, explain returns of the portfolios formed on these firm characteristics.[18] Therefore, the effects of beta herding on cross-sectional asset returns are distinct from those of sentiment, despite the close connection between sentiment and beta herding.

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[17] This discrepancy can be explained by two distinct differences in the calculation of betas. First, in this study we calculate betas in the presence of SML, HML, RAW, and CMA. Therefore our betas are less likely to be related to size or distress. Second, by comparing the sizes of the decile portfolios formed on estimated betas and standardized-betas (not reported), we find that small stocks whose estimated betas are high tend to have larger standard errors and thus, the standardized-betas become smaller.

[18] The coefficients on the BW sentiment measure are similar to those reported by Baker and Wurgler (2006) when Fama-French three factors and momentum.

4.5. Robustness of the results to other estimates of betas or estimation windows

The first test focuses on the robustness with respect to other asset pricing models. Our main results in Tables 4 and 5 may be limited because the Fama-French five-factor model is arbitrary although it can explain cross-sectional stock returns in practice (Fama and French, 2015). According to the CAPM, beta is the only risk that should be priced. The beta we estimate using the Fama-French five-factor model is equivalent to the estimate of the CAPM beta only when other four factors are orthogonal to the excess market return. If asset returns are explained by multi-factor models as in Merton (1973) and Ross (1976) and the excess market return is just one of the factors, then the sensitivity of asset returns with respect to the excess market return should be measured in the presence of these other factors because betas are closely related to many firm characteristics that have been known to predict cross-sectional asset returns (Fama and French, 1993; Kogan and Papanikolaou, 2013; Harvey, Liu and Zhu, 2016). Theory, however, does not directly tell us how many factors are required for asset returns or what these factors are. We use the nine empirical factors in subsection 4.3 (Table 6) in addition to the excess market return.

The results in Table 8 are not different from those in Tables 5 and 6. Most coefficients on the lagged beta herd measure are negative and some are significant, in particular when the forecasting horizon increases. The results with value-weighted portfolios (not reported) are weaker than those with equally weighted portfolios but are not in consistent with those with the Fama-French five-factor model in Table 5. Therefore, as in Baker, Bradley, and Taliaferro (2014), negative risk-adjusted returns increase with adverse beta herding regardless of the market model, five- or ten-factor models. Once again, the low-beta anomaly in the market model disappears when beta herding is included as an explanatory variable. Therefore, the large negative risk-adjusted returns of high-minus-low beta portfolios are created by unusually large cross-sectional dispersion of betas through investors' under-confidence or pessimistic view about the direction of the entire market.

As a second robustness test, we investigate if our results are robust when standardized-betas and beta herd measure are estimated using different estimation windows. The results with two different windows (not reported), 84 and 48 months, are similar to those with 60 months window (Table 5): most coefficients on the lagged herd measure are negative.[19]

5. Beta herding and economic events

With thousands of stocks, the confidence region calculated by equation (15) is so tight that we observe many significant but small changes in herding activity. Rather than focusing on all of these minor changes in beta herding, we identify periods of high and low H_t^* as well as major turning points and connect those to economic events anecdotally, which provides insight into what we might expect from the herd measure.

5.1. Beta herding and economic events

There were several periods when H_t^* was significantly lower than other periods: 1) late 1968-1969, 2) 1974-1975 (a few years following the first Oil Shock in 1973), 3) 1981-1982 (a few years following the second Oil Shock in 1979), 4) 1985-1987 (a few years before the 1987 Crash), 5) 1996-1998 (bull period before the Russian Crisis in 1998), 6) 1999-2002 (the boom and bust period around 2000), and 7) 2007-2008 (just before the 2008 credit crisis). Among these periods of high herding activity, the market was bullish only in periods 2), 4), 5)

[19] The details of the results can be obtained upon request from the authors.

and 7), but was bearish in the other high beta herding periods. This result is consistent with the weak statistical evidence linking market movements and beta herding found in Table 3.

We further investigate whether or not changes in business cycle are linked to the dynamics of beta herding. Seven change points from expansion to recession and from recession to expansion since 1962 are identified from the National Bureau of Economic Research (NBER). Herd measures are then aligned for the change events and the average values of herd measure are calculated. Figure 2A shows that for both cases there is no significant change in beta herding due to the business cycle. We also perform the same procedure for the period from 1932 (the herd measure is calculated with CRSP data and reported in Figure 3), but the results are similar. Business cycles do not appear to affect the dynamics of beta herding. This is consistent with the results reported in Table 3 where none of the macroeconomic variables including the NBER recession dummy can explain beta herding.

However, some economic events do appear to change the direction of herding. For example, we identify eleven such events and plot H_t^* before and after these events in Figure 2B. Following the two oil shocks in the 1970s beta herding began to increase. After the 1979 Oil Shock, the sharp interest rate rise in 1980 increased beta herding further. Strong herding existed during the early 1980s' bear market, which ended in 1982 when interest rates began to fall and the market became bullish. On the other hand, after the two events, the 1987 Crash and the 1998 Russian Crisis, both of which occurred during high beta herding periods, herding decreased. Note that neither of these events changed the direction of the business cycle. Years such as 1985, 1992 and 2013 were bullish when investor's optimistic view prevails.

There was a dramatic change in beta herding at the end of the 2000s. Herding began to increase from the end of 2005 and was accelerated by the 'Quant Meltdown' in 2007, which refers to the unprecedented losses experienced by quantitative long/short equity hedge funds during August 2007. Khandani and Lo (2011) suggest that a 'coordinated' deleveraging of similarly constructed portfolios is to be blamed for the meltdown. The coordination of arbitrageurs would increase market-wide herding, as arbitrage trading would be seriously limited during these periods. The increased herding suddenly disappeared in the summer of 2008 at the onset of the credit crisis.

5.2. Adverse beta herding during crises

Our evidence does not support the view that beta herding through investor overconfidence or sentiment occurs when financial markets are in stress (or in crisis). In so far as individual asset returns move following their systematic risks, the market-wide negative returns are rational. Only when individual asset returns move in one direction excessively, thus violating the equilibrium relation with the market returns, can we call it irrational. Figure 1 shows that it is the estimation error that leads to sharp decreases in H_t^*.[20]

[20] The large shifts in the estimation errors explain why many empirical studies on herding in advanced markets have found little concrete evidence of herd behavior. However, in the South Korean case, Kim and Wei (2002) and Choe, Kho, and Stulz (1999) study herd behavior around the Asian Crisis in 1997 and find some evidence during the Crisis. These studies use the measure developed by Lakonishok, Shleifer, and Vishny (1992), which focuses on a subset of market participants. Therefore, we cannot conclude that their results are inconsistent with ours as our measure considers beta herding in the whole market, rather than a subset of participants. Chang, Cheng and Khorana (2000), using a variant of the method developed by Christie and Huang (1995), suggest the presence of herding in emerging markets such as South Korea and Taiwan, but failed to find such evidence in the US, Hong Kong and Japanese markets. Other studies suggest evidence of herding in industries or in international markets

Adverse beta herding occurs when investors are under-confident about the stability and outlook of the future stock market. This would also explain how sentiment contributes to adverse beta herding in crises. During the crises in 1987, 1998, and 2008, investors became pessimistic and lost confidence in their views, resulting in adverse beta herding. Our model and empirical results support that investors' pessimism and loss of confidence increases adverse beta herding which create the low-beta anomaly.

5.3. Beta herding in portfolios and before 1967

The dynamics of the beta-based herd measure (H_t^{O}) calculated with the three portfolios (Fama-French portfolios formed on size, book-to-market, investment, and profitability, and 49 industry portfolios) are compared with those of H_t^* calculated with individual stocks (CRSP data) in Figure 3 for the period from January 1932 to December 2016. To increase robustness of our results we use Fama-French 25 portfolios formed on size and book-to-market together with their 25 portfolios formed on operating profitability and investment. The patterns prior to 1967 support our previous argument that beta herding is created by a clear homogeneity of view in the direction in which the market is likely to move.

They all move in similar ways. When the individual stocks show high levels of beta herding, these portfolios also show high levels of beta herding. The relation between individual stocks and the 49 industry portfolios is particularly strong with a correlation coefficient of 0.68. In addition, the correlation coefficients between H_t^* calculated with individual stocks and H_t^{O} with the two firm characteristic based portfolios also range from 0.4 to 0.5.

(Choi and Sias, 2009)

The results with portfolios also support the standardized-beta herd measure. Since H_t^{O} calculated with portfolios is less likely to be affected by estimation error than that calculated with individual stocks, the correlation between H_t^* and H_t^{O} should be high when they are calculated with portfolios. Consistent with the expectation, the rank correlation between these two measures of the 49 industry portfolios is 0.44 that is much higher than -0.15 in Table 2 we obtain with individual stocks.

6. Conclusions

Beta herding, as we propose, measures the cross-sectional dispersion in betas. When high betas are downward-biased and low betas are upward-biased, asset returns are more likely to track market movements. The existence of beta herding and adverse beta herding indicates that individual assets are mispriced, when equilibrium beliefs are suppressed. Our measure captures the impact of herding on asset prices rather than herding by individuals or a small group of investors, and thus is different from herd measures proposed by Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), and Park and Sabourian (2011).

We have applied our measure to the US stock market and found that beta herding disappeared during crises such as the 1987 Crash, the 1998 Russian Crisis, and the 2008 Credit Crisis. Contrary to a common belief that beta herding is significant when the market is under pressure, we find that beta herding becomes more apparent when investors feel overconfident regarding the future direction of the market. Once a crisis appears, beta herding weakens substantially.

One important question is whether beta herding predicts cross-sectional asset returns.

Fama and French (1992, 1993) show that beta is not priced. However, as predicted by the low-beta anomaly of Baker, Bradley, and Taliaferro (2014), beta does matter conditionally on beta herding: high beta stocks show lower returns than low beta stocks after adverse beta herding. Therefore, the anomaly disappears when beta herding is considered.

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Appendix

Proof of Lemma 1

Under the assumption that r_{it+1} and $E_t^b(r_{mt+1}|s_{mt})$ follow a jointly normal distribution, the conditional expectation of r_{it+1} given $E_t^b(r_{mt+1}|s_{mt})$ is

$$E_t\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt})\right) = \frac{cov_t(E_t^b(r_{mt+1}|s_{mt}), r_{it+1})}{var(E_t^b(r_{mt+1}|s_{mt}))} E_t^b(r_{mt+1}|s_{mt})$$
$$= \frac{cov_t(s_{mt}, r_{it+1})}{w_{bt} var(s_{mt})}(\mu_m + w_{bt}s_{mt})$$
$$= \frac{cov_t(\varepsilon_{mt+1}, r_{it+1})}{w_{bt}(\sigma_{m\varepsilon t}^2 + \sigma_{m\epsilon t}^2)}(\mu_m + w_{bt}s_{mt}),$$

from which the result in equation (1) can be obtained. QED.

Proof of Lemma 2

Beta of asset i is

$$\beta_{it}^b = \frac{E_t^b\left(r_{it+1}\middle|E_t^b(r_{mt+1}|s_{mt}, \delta_{mt})\right)}{E_t^b(r_{mt+1}|s_{mt}, \delta_{mt})} = \frac{\gamma_t^*\beta_{it}(\mu_m + w_{bt}s_{mt}) + \delta_{mt}}{(\mu_m + w_{bt}s_{mt}) + \delta_{mt}} = \frac{\gamma_t^*\beta_{it} + \delta_{mt}^{**}}{1 + \delta_{mt}^{**}},$$

where $\delta_{mt}^{**} = \frac{\delta_{mt}}{(\mu_m + w_{bt}s_{mt})}$. The result in equation (9) can be obtained using $E_c(\beta_{it}^b) = \frac{\gamma_t^* + \delta_{mt}^{**}}{1 + \delta_{mt}^{**}}$. QED.

Proof of Theorem 1

With the assumption of $\hat{\beta}_{it}^b \sim N(\beta_{it}^b, \sigma_{\beta_{it}^b})$ and τ observations, we obtain the following non-central t distribution with the degrees of freedom $\tau - K - 1$:

$$\frac{\hat{\beta}_{it}^b - \overline{\hat{\beta}_{it}^b}}{\hat{\sigma}_{\hat{\beta}_{it}^b}} \sim t(\tau - K - 1; \delta_{it}^*),$$

where δ_{it}^* is a non-centrality parameter, i.e., $\delta_{it}^* = (\beta_{it}^b - \mathrm{E}(\beta_{it}^b))/\sigma_{\beta_{it}^b}$. Let $B_{it}^* \equiv (\hat{\beta}_{it}^b - 1)/\hat{\sigma}_{\hat{\beta}_{it}^b}$, and thus $B_{it}^* \sim N(\delta_{it}^*, 1)$. Let $\mathbf{B}_t^* = (B_{1t}^* \quad B_{2t}^* \quad . \quad B_{Nt}^*)'$. Then with the classical LS assumption, for a large $\tau - K - 1$,

$$\underset{N\times N}{\mathbf{B}_t^*} \sim N\left(\underset{N\times 1}{\boldsymbol{\delta}_t^*}, \underset{N\times N}{\mathbf{V}_t^*}\right),$$

where $\boldsymbol{\delta}_t^* = (\delta_{1t}^* \quad \delta_{2t}^* \quad . \quad \delta_{Nt}^*)'$, and $\mathbf{V}_t^*$ is covariance matrix of $\mathbf{B}_t^*$.

In general, we may not assume that the matrix $\mathbf{V}_t^*$ is fully ranked, since a large number of equities could mean $\tau - K - 1 < N$, suggesting the $(N \times N)$ variance-covariance matrix $\mathbf{V}_t^*$ being singular. Let $\mathbf{Z} = \mathbf{C}'\mathbf{B}_t^*$, where $\mathbf{C}$ is the $(N \times N)$ matrix of the eigenvectors of the symmetric matrix of $\mathbf{V}_t^*$, i.e., $\mathbf{V}_t^* = \mathbf{C}\boldsymbol{\Lambda}\mathbf{C}'$ and $\boldsymbol{\Lambda}$ is the $(N \times N)$ diagonal matrix of the eigenvalues. Note that the eigenvalues are sorted in descending order and the eigenvectors are also sorted in accordance to the sorted eigenvalues. Then using $\mathbf{C}'\mathbf{C} = \mathbf{I}$ and

$$E(\mathbf{Z}) = \mathbf{C}'E(\mathbf{B}_t^*) = \mathbf{C}'\boldsymbol{\delta}_t^*$$

$$
\begin{aligned}
Var(\mathbf{Z}) &= E[(\mathbf{C}'\mathbf{B}_t^* - \mathbf{C}'\boldsymbol{\delta}_t^*)(\mathbf{C}'\mathbf{B}_t^* - \mathbf{C}'\boldsymbol{\delta}_t^*)'] \\
&= \mathbf{C}'\mathbf{V}_t^*\mathbf{C} \\
&= \boldsymbol{\Lambda},
\end{aligned}
$$

we have $\mathbf{Z} \sim (\boldsymbol{\delta}_t^{*A}, \boldsymbol{\Lambda})$, where $\boldsymbol{\delta}_t^{*A} = \mathbf{C}'\boldsymbol{\delta}_t^*$. When the rank (R) of the matrix $\mathbf{V}$ is less than N, i.e., $R \leq N$, the first R variables in the vector $\mathbf{Z}$ are normally distributed, $z_i \sim N(\delta_{it}^{*A}, \lambda_i)$, where z_i is the ith variable of $\mathbf{Z}$, δ_{it}^{*A} is the ith element of vector $\boldsymbol{\delta}_t^{*A}$, and λ_i is the ith eigenvalue of the diagonal matrix $\boldsymbol{\Lambda}$. On the other hand, the remaining $N - R$ variables of z_i, $i = R+1, \ldots, N$, are just constants since $\lambda_i = 0$ for $i = R+1, \ldots, N$. Thus we have

$$
\begin{aligned}
\mathbf{B}_t^{*\prime}\mathbf{B}_t^* &= (\mathbf{CZ})'\mathbf{CZ} \\
&= \mathbf{Z}'\mathbf{C}'\mathbf{CZ} \\
&= \mathbf{Z}'\mathbf{Z} \\
&= \sum_{i=1}^{R} z_i^2 + \sum_{i=R+1}^{N} z_i^2.
\end{aligned}
$$

Since $z_i \sim N(\delta_{it}^{*A}, \lambda_i)$ is independent (orthogonal) of z_j for all $i \neq j$ for $i, j \leq R$, the first component is

$$\sum_{i=1}^{R} z_i^2 \sim \chi^2(R; \delta_k^R),$$

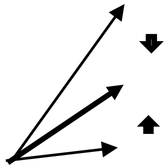
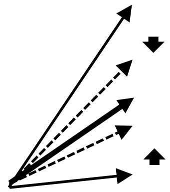
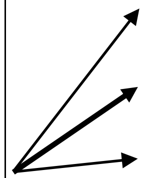
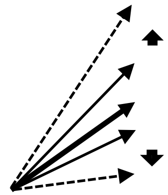
where δ_k^R is the non-centrality parameter, i.e., $\delta_k^R = \sum_{i=1}^{R} (\delta_{it}^{*A})^2/\lambda_i$. The second component is a constant, i.e., $c \equiv \sum_{i=R+1}^{N} z_i^2 = \sum_{i=R+1}^{N} (\delta_{it}^{*A})^2$. Thus

$$\mathbf{B}_t^{*\prime}\mathbf{B}_t^* \sim \chi^2(R; \delta_k^R) + c.$$

Therefore, our herd measure follows

$$h_{kt} = \frac{1}{N_t}\mathbf{B}_t^{*\prime}\mathbf{B}_t^* \sim \frac{1}{N_t}[\chi^2(R; \delta_k^R) + c]. \qquad \text{QED.}$$

Table 1 Beta herding, cross-sectional bias in beta, sentiment, and expected returns

	Perfect beta herding	Beta herding	No beta herding	Adverse beta herding
Overconfidenc and sentiment	$\delta_{mt}^{**} \to \infty$, or $\gamma_t^* \to 0$	$\delta_{mt}^{**} > 0$, or $0 < \gamma_t^* < 1$	$\delta_{mt}^{**} = 0$, or $\gamma_t^* = 1$	$\delta_{mt}^{**} < 0$, or $\gamma_t^* > 1$
β_{it}^b	1	$\beta_{it} < \beta_{it}^b < 1, for\ \beta_{it} < 1$ $1 < \beta_{it}^b < \beta_{it}, for\ \beta_{it} > 1$	β_{it}	$\beta_{it}^b < \beta_{it} < 1, for\ \beta_{it} < 1$ $1 < \beta_{it} < \beta_{it}^b, for\ \beta_{it} > 1$
$E_t^b(r_{it+1})$	$E_t^b(r_{mt+1})$	$E_t(r_{it}) < E_t^b(r_{it}), for\ \beta_{it} < 1$ $E_t^b(r_{it}) < E_t(r_{it}), for\ \beta_{it} > 1$	$E_t(r_{it})$	$E_t^b(r_{it}) < E_t(r_{it}), for\ \beta_{it} < 1$ $E_t(r_{it}) < E_t^b(r_{it}), for\ \beta_{it} > 1$
Bias in expected excess returns and betas				

The figure summarizes four cases that describe the effects of investor overconfidence and sentiment on cross-sectional asset prices. Thick solid lines represent the market, the upper and lower thin solid lines represent high and low beta stocks, respectively, and the upper and lower dotted lines represent biases in high and low beta stocks, respectively.

Table 2   Properties of Beta Herd Measure

We use the monthly data file from the merged Center for Research in Security Prices (CRSP) - Compustat database for common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. Using monthly observations from January 1962 to December 2016 and rolling windows of 60 months, we obtain 600 monthly herd measures from January 1967 to December 2016. Every month betas are estimated in the market model or the Fama-French five-factor model. The beta-based herd measure is calculated with the cross-sectional variance of least square estimates of betas, and the standardized herd measure is calculated with the cross-sectional variance of t statistics of betas that are calculated with the Newey-West heteroskedastic adjusted standard errors. We use stocks whose prices are higher than $1 (non-penny stocks) at the estimation month and whose past 60 (minimum 24) monthly observations are available. We omit stocks whose turnovers (trading volume divided by shares outstanding) belong to the bottom 1% or whose volatilities (standard deviations of returns) are excessively volatile or little volatility at all (top and bottom 1%) during the past 60 months. To minimize any adverse effects from a small number of extreme beta estimates on our analysis, we use a statistical trimming process where the top and bottom 1% of beta estimates and standardized-beta estimates are omitted in our calculation of the beta herd measure. The bold numbers represent significance at the 5% level.

	Beta-Based Herd Measure		Standardized Herd Measure	
	Market Model (A)	Fama-French Five-factor Model (B)	Market Model (C)	Fama-French Five-factor Model (B)
Mean	0.360	0.327	4.673	2.405
Standard Deviation	0.195	0.152	1.566	0.533
Skewness	1.497	0.689	0.878	0.355
Excess Kurtosis	4.496	2.279	3.681	2.319
Jarque-Bera Statistics	**280.05**	**60.38**	**88.61**	**24.19**
Spearman Rank Correlations between A and B, and C and D	**0.963**		**0.527**	
Spearman Rank Correlation between Cross-sectional Standard Deviations of Betas and t-Statistics	Between A and C	Between B and D		
	0.317	**-0.146**		

Table 3 Regression of Beta Herding in Individual Stocks on Various Variables

The beta-based and standardized herd measures are calculated by rolling windows of 60 (minimum 24) months using the Fama-French five-factor model to obtain 600 monthly observations from January 1967 to December 2016. These measures are then regressed on various explanatory variables. Rm and Vm represent excess market return and market volatility respectively. DY and RF represent the dividend yield and the 1 month Treasury bill rate, whereas TS and CS show the term spread (difference between 10 years Treasury Bond and 1 year Treasury Bill rate) and the credit spread (difference between Moody's Aaa and Baa rated bond yields) respectively. CAY, CPI, IP, Cons, Unemp, and NBER represents the Lettau and Ludvigson (2001) consumption-wealth ratio, the monthly inflation rate, the growth in industrial production, the growth in consumption of durables, nondurables, and services, the unemployment rate, and a dummy variable for NBER recessions. These data are obtained from the Federal Reserve Bank of St. Louis. CVEE (the cross-sectional average of estimation errors) is calculated by taking the cross-sectional average value of the squared standard errors of estimated betas. The numbers in brackets are the Newey-West heteroskedastic adjusted standard errors. The bold numbers represent significance at the 5% level.

Constant	Lagged Herd Measure	CVEE	Rm	Vm	TB	CS	TS	DY	NBER	Unemp	CPI	IP	Cons	CAY	*adj* R^2
A. Beta-Based Herd Measure															
0.0026	**0.9925**														0.986
(0.0014)	(0.0051)														
0.0052	**0.9059**	**0.1060**													0.986
(0.0019)	(0.0231)	(0.0268)													
0.0069	**0.9161**	**0.0976**	**0.0008**	-0.0009											0.988
(0.0029)	(0.0199)	(0.0240)	(0.0003)	(0.0008)											
-0.0019	**0.8469**	**0.1763**			-0.0012	0.0001	0.0001	0.0004	-0.0054	0.0020	0.0037	-0.0022	0.0021	-0.0006	0.988
(0.0061)	(0.0403)	(0.0458)			(0.0008)	(0.0035)	(0.0019)	(0.0014)	(0.0032)	(0.0012)	(0.0037)	(0.0014)	(0.0012)	(0.0004)	
0.0094	**0.8601**	**0.1555**	**0.0006**	-0.0014	-0.0016	0.0043	-0.0009	-0.0008	-0.0010	0.0014	0.0040	-0.0013	0.0012	0.0001	0.988
(0.0067)	(0.0353)	(0.0383)	(0.0002)	(0.0009)	(0.0008)	(0.0040)	(0.0019)	(0.0015)	(0.0036)	(0.0010)	(0.0041)	(0.0013)	(0.0012)	(0.0004)	
B. Standardized-Beta Herd Measure															
0.0462	**0.9809**														0.962
(0.0211)	(0.0090)														
0.0837	**0.9736**	**-0.0830**													0.962
(0.0274)	(0.0098)	(0.0328)													
0.0419	**0.9738**	**-0.1058**	0.0009	**0.0115**											0.964
(0.0237)	(0.0090)	(0.0341)	(0.0013)	(0.0028)											
0.2459	**0.9452**	**-0.2565**			**-0.0083**	0.0333	-0.0072	-0.0133	0.0009	0.0005	0.0124	0.0116	-0.0148	**0.0063**	0.964
(0.0605)	(0.0127)	(0.0661)			(0.0037)	(0.0191)	(0.0076)	(0.0096)	(0.0176)	(0.0050)	(0.0150)	(0.0100)	(0.0092)	(0.0028)	
0.1381	**0.9517**	**-0.1976**	0.0010	**0.0120**	-0.0042	-0.0016	0.0027	-0.0032	-0.0230	0.0014	0.0150	0.0082	-0.0108	0.0016	0.966
(0.0576)	(0.0119)	(0.0636)	(0.0013)	(0.0035)	(0.0036)	(0.0217)	(0.0079)	(0.0101)	(0.0163)	(0.0047)	(0.0160)	(0.0086)	(0.0082)	(0.0028)	

Table 4 Buy-and-hold returns over 12 months from the portfolio formation conditioning on herding states

From January 1967 to December 2015, every month we form decile portfolios on standardized-betas using NYSE breakpoints, and calculate the equally weighted and value weighted buy-and-hold return for the following 12 months after the formation. The sample period is divided into three herding states, i.e., adverse herding, no herding, and herding, identified by the top 20%, middle 60%, and bottom 20% of the standardized-beta herd measure, respectively. The Fama-French five factors are used for the pre- and port-formation betas and beta herd measure. The numbers in the brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

A. Equally weighted buy-and-hold returns of decile portfolios formed on standardized-betas (Five-factor model)

		Low	2	3	4	5	6	7	8	9	High	High-Low
Unconditional Performance	Raw Returns	**12.040**	**12.990**	**14.102**	**13.860**	**13.671**	**13.604**	**13.165**	**13.062**	**12.664**	**11.998**	-0.042
		(2.144)	(2.435)	(2.591)	(2.762)	(2.836)	(2.880)	(2.935)	(3.007)	(3.045)	(3.188)	(2.229)
	Alphas	2.328	**2.122**	**1.644**	**1.480**	1.212	1.067	0.430	0.347	-1.431	**-3.641**	**-5.969**
		(1.174)	(0.721)	(0.607)	(0.670)	(0.732)	(0.666)	(0.726)	(1.005)	(1.142)	(1.428)	(2.356)
	Betas	**0.841**	**1.006**	**1.126**	**1.158**	**1.197**	**1.201**	**1.267**	**1.274**	**1.315**	**1.415**	**0.574**
		(0.063)	(0.047)	(0.035)	(0.042)	(0.040)	(0.045)	(0.045)	(0.059)	(0.059)	(0.088)	(0.140)
Adverse Herding (Top 20%)	Raw Returns	**12.482**	**12.375**	**12.047**	**11.654**	**11.146**	**11.572**	10.620	10.792	8.948	8.054	-4.429
		(4.154)	(4.816)	(5.144)	(5.195)	(5.655)	(5.357)	(5.538)	(5.658)	(5.637)	(5.921)	(3.694)
	Alphas	**10.364**	**7.405**	**4.959**	**3.276**	**1.548**	**3.277**	1.809	-0.420	**-5.212**	**-6.758**	**-17.122**
		(2.181)	(0.636)	(0.746)	(0.650)	(0.682)	(1.088)	(1.550)	(2.496)	(2.512)	(2.783)	(4.768)
	Betas	**0.480**	**0.739**	**0.907**	**0.986**	**1.104**	**1.028**	**1.070**	**1.206**	**1.344**	**1.427**	**0.948**
		(0.098)	(0.035)	(0.045)	(0.035)	(0.046)	(0.053)	(0.073)	(0.107)	(0.104)	(0.133)	(0.218)
No Herding (Middle 60%)	Raw Returns	**12.108**	**14.079**	**15.357**	**15.498**	**15.499**	**15.364**	**15.380**	**15.466**	**14.840**	**14.519**	2.411
		(2.458)	(2.869)	(3.089)	(3.442)	(3.486)	(3.584)	(3.673)	(3.762)	(3.787)	(4.129)	(2.973)
	Alphas	0.642	**1.869**	**1.963**	**2.153**	**2.243**	1.334	1.604	1.766	0.823	-1.169	-1.811
		(1.230)	(0.850)	(0.674)	(0.987)	(1.036)	(0.984)	(1.118)	(1.122)	(1.498)	(1.850)	(2.696)
	Betas	**0.857**	**1.042**	**1.179**	**1.232**	**1.269**	**1.303**	**1.353**	**1.370**	**1.406**	**1.524**	**0.667**
		(0.078)	(0.061)	(0.048)	(0.065)	(0.057)	(0.056)	(0.060)	(0.079)	(0.084)	(0.134)	(0.200)
Herding (Bottom 20%)	Raw Returns	**11.444**	10.289	12.185	10.933	10.458	10.159	8.820	7.908	9.471	7.979	-3.465
		(5.582)	(5.807)	(6.198)	(6.155)	(6.386)	(6.582)	(6.909)	(6.503)	(6.605)	(6.298)	(3.108)
	Alphas	3.920	2.318	**2.610**	**4.207**	**3.153**	**3.433**	1.901	1.754	-0.392	-0.603	-4.522
		(2.151)	(1.432)	(0.989)	(1.422)	(1.339)	(1.363)	(1.676)	(1.657)	(2.211)	(2.639)	(4.233)
	Betas	**0.898**	**1.042**	**1.125**	**1.061**	**1.130**	**1.037**	**1.139**	**1.100**	**1.207**	**1.165**	0.268
		(0.082)	(0.046)	(0.041)	(0.060)	(0.053)	(0.056)	(0.053)	(0.067)	(0.097)	(0.118)	(0.191)

B. Value weighted buy-and-hold returns of decile portfolios formed on standardized-betas (Five-factor model)

		Low	2	3	4	5	6	7	8	9	High	High-Low
Unconditional Performance	Raw Returns	**6.334**	**8.153**	**8.244**	**6.588**	**6.819**	**7.745**	**7.260**	**6.867**	**6.529**	**7.549**	1.215
		(2.102)	(2.121)	(2.208)	(2.136)	(2.234)	(2.320)	(2.333)	(2.293)	(2.471)	(2.743)	(2.224)
	Alphas	**3.374**	**3.970**	**1.648**	-0.085	0.750	0.616	-1.019	**-2.936**	**-3.285**	**-5.323**	**-8.697**
		(1.274)	(0.838)	(0.708)	(0.683)	(0.576)	(0.588)	(0.753)	(0.864)	(1.208)	(1.005)	(2.088)
	Betas	**0.731**	**0.835**	**1.009**	**0.988**	**0.991**	**1.060**	**1.111**	**1.154**	**1.197**	**1.335**	**0.604**
		(0.055)	(0.035)	(0.023)	(0.040)	(0.030)	(0.034)	(0.032)	(0.037)	(0.052)	(0.076)	(0.110)
Adverse Herding (Top 20%)	Raw Returns	**11.721**	**12.791**	**10.649**	**9.410**	**9.137**	**11.358**	**10.798**	**8.202**	**9.472**	6.897	-4.823
		(2.296)	(2.830)	(3.354)	(3.295)	(3.920)	(3.810)	(4.118)	(3.257)	(3.322)	(4.618)	(3.263)
	Alphas	5.394	2.746	**-0.165**	**-0.454**	**-0.771**	**3.379**	**1.319**	**-6.156**	**-5.275**	**-6.923**	**-12.317**
		(1.645)	(1.322)	(1.436)	(1.683)	(0.723)	(0.971)	(1.158)	(1.555)	(1.439)	(1.318)	(2.126)
	Betas	**0.623**	**0.940**	**1.043**	**1.036**	**1.079**	**0.979**	**1.090**	**1.257**	**1.286**	**1.266**	**0.643**
		(0.105)	(0.054)	(0.072)	(0.074)	(0.071)	(0.067)	(0.066)	(0.062)	(0.121)	(0.079)	(0.153)
No Herding (Middle 60%)	Raw Returns	**6.719**	**7.835**	**8.023**	**7.082**	**7.731**	**8.354**	**8.143**	**8.250**	**8.696**	**9.432**	2.713
		(2.298)	(1.984)	(2.299)	(2.196)	(2.255)	(2.407)	(2.723)	(2.774)	(2.942)	(3.522)	(2.754)
	Alphas	**1.538**	**2.979**	**1.911**	**0.583**	**1.105**	**0.990**	**-0.444**	**-1.483**	**-2.670**	**-3.092**	-4.629
		(1.782)	(1.529)	(0.922)	(1.080)	(0.648)	(0.650)	(0.987)	(0.930)	(1.416)	(1.626)	(3.072)
	Betas	**0.765**	**0.805**	**0.969**	**0.950**	**0.982**	**1.038**	**1.152**	**1.196**	**1.284**	**1.423**	**0.658**
		(0.068)	(0.048)	(0.032)	(0.039)	(0.035)	(0.033)	(0.032)	(0.028)	(0.053)	(0.107)	(0.155)
Herding (Bottom 20%)	Raw Returns	0.407	4.986	6.773	2.612	2.044	2.724	1.490	1.559	-2.542	2.513	2.105
		(6.700)	(7.682)	(7.770)	(7.178)	(7.578)	(7.547)	(6.456)	(5.964)	(6.310)	(6.280)	(4.425)
	Alphas	3.131	**5.335**	**5.731**	0.237	1.823	1.363	-1.387	**-5.204**	**-7.539**	**-5.484**	**-8.615**
		(2.251)	(2.236)	(1.654)	(1.508)	(1.212)	(1.577)	(1.593)	(1.431)	(1.737)	(1.980)	(3.580)
	Betas	**0.687**	**0.919**	**0.999**	**1.072**	**0.971**	**1.039**	**1.002**	**1.114**	**1.074**	**1.153**	**0.467**
		(0.068)	(0.063)	(0.058)	(0.068)	(0.027)	(0.078)	(0.043)	(0.059)	(0.048)	(0.068)	(0.121)

Table 5 The effects of beta herding on standardozed beta-sorted portfolios

For the sample period from January 1967 to December 2016, every month we form quintile portfolios sorted on standardized-betas using non-penny stocks (>$1) and NYSE breakpoints. The post-formation returns of the high-minus-low standardized-beta quintile portfolio is regressed on lagged beta herding in the presence of other control variables:

$$r^{\beta}_{High,t+f} - r^{\beta}_{Low,t+f} = \alpha + c_1 H^*_t + \sum_{k=2}^{K} c_{\mathrm{k}} f_{k,t+f} + \varepsilon_{i,t+f},$$

$$r^{\beta}_{High,t+f} - r^{\beta}_{Low,t+f} = \alpha + c^+_t H^*_t I_{\mathrm{t}} + c^-_t H^*_t (1 - I_{\mathrm{t}}) + \sum_{k=2}^{K} c_{\mathrm{k}} f_{k,t+f} + \varepsilon_{i,t+f},$$

where the forecasting horizon is set to f=3, 6, 9, 12, 15, 18, and 24, which are represented by 3M, 9M, … and 24M, respectively, and $I_{\mathrm{t}} = 1$ if $H^*_t > \frac{1}{T}\sum_{t=1}^{T} H^*_t$ and $I_{\mathrm{t}} = 0$ otherwise. Adverse herding represents heard measure larger than the average level of herd measure over the sample period whereas herding represents heard measure less than the average level of herd measure over the sample period. Overlapping portfolios are constructed to increase the power of the tests as in Jegadeesh and Titman (2001). The control variables include EMR, SMB, HML, RMW, and CMA represent the excess market return, size, book-to-market, operating profitability, and investment factor returns from Kenneth French's data library, respectively. The numbers in the brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

	Average Returns	Constant	Herd Measure (H^*_t)	Adverse Herding ($H^*_t I_{\mathrm{t}}$)	Herding ($H^*_t(1-I_{\mathrm{t}})$)	EMR	SMB	HML	RAW	CMA	*Adj R*^{2}
A. Equally-Weighted Portfolio Returns (Five-factor model)											
3M	0.049	**-0.291**				**0.525**	**0.171**	0.008	0.018	0.062	0.57
	(0.146)	(0.102)				(0.040)	(0.053)	(0.082)	(0.077)	(0.106)	
9M	0.029	**-0.301**				**0.498**	**0.185**	0.014	0.038	0.046	0.57
	(0.139)	(0.095)				(0.038)	(0.052)	(0.080)	(0.066)	(0.093)	
12M	0.013	**-0.316**				**0.486**	**0.186**	0.004	0.049	0.063	0.58
	(0.135)	(0.092)				(0.036)	(0.050)	(0.075)	(0.063)	(0.089)	
15M	0.001	**-0.322**				**0.474**	**0.187**	-0.002	0.051	0.071	0.58
	(0.132)	(0.089)				(0.034)	(0.048)	(0.070)	(0.060)	(0.084)	
18M	-0.004	**-0.318**				**0.462**	**0.187**	-0.008	0.046	0.072	0.58
	(0.129)	(0.087)				(0.033)	(0.046)	(0.067)	(0.056)	(0.080)	
24M	0.001	**-0.300**				**0.447**	**0.178**	-0.015	0.047	0.071	0.58
	(0.125)	(0.085)				(0.031)	(0.045)	(0.063)	(0.053)	(0.076)	
3M	0.049	0.009	-0.123			**0.526**	**0.171**	0.007	0.017	0.061	0.57
	(0.146)	(0.526)	(0.209)			(0.040)	(0.053)	(0.082)	(0.077)	(0.105)	
9M	0.029	0.317	-0.254			**0.498**	**0.183**	0.015	0.036	0.041	0.57
	(0.139)	(0.580)	(0.229)			(0.038)	(0.051)	(0.080)	(0.066)	(0.093)	
12M	0.013	0.479	-0.328			**0.486**	**0.185**	0.006	0.048	0.053	0.58
	(0.135)	(0.545)	(0.217)			(0.035)	(0.049)	(0.074)	(0.063)	(0.089)	
15M	0.001	0.745	**-0.442**			**0.474**	**0.186**	0.001	0.052	0.055	0.58
	(0.132)	(0.534)	(0.217)			(0.034)	(0.048)	(0.070)	(0.059)	(0.085)	
18M	-0.004	0.628	-0.392			**0.461**	**0.186**	-0.005	0.047	0.056	0.58
	(0.129)	(0.492)	(0.202)			(0.032)	(0.046)	(0.067)	(0.056)	(0.081)	
24M	0.001	0.510	-0.338			**0.447**	**0.177**	-0.011	0.044	0.057	0.58
	(0.125)	(0.424)	(0.176)			(0.031)	(0.045)	(0.064)	(0.052)	(0.076)	
30M	0.022	0.600	**-0.362**			**0.435**	**0.169**	-0.022	0.034	0.055	0.58
	(0.122)	(0.402)	(0.168)			(0.030)	(0.044)	(0.062)	(0.048)	(0.073)	
36M	0.039	0.314	-0.231			**0.423**	**0.169**	-0.032	0.025	0.056	0.59
	(0.119)	(0.384)	(0.161)			(0.030)	(0.043)	(0.061)	(0.046)	(0.072)	
3M	0.049	-0.013		-0.116	-0.112	**0.526**	**0.171**	0.007	0.017	0.061	0.57
	(0.146)	(0.975)		(0.339)	(0.466)	(0.040)	(0.053)	(0.082)	(0.078)	(0.105)	
9M	0.029	1.321		-0.580	-0.775	**0.500**	**0.186**	0.017	0.039	0.040	0.57
	(0.139)	(1.040)		(0.369)	(0.487)	(0.038)	(0.051)	(0.080)	(0.066)	(0.093)	
12M	0.013	1.621		**-0.700**	**-0.922**	**0.486**	**0.187**	0.014	0.049	0.047	0.58
	(0.135)	(0.968)		(0.344)	(0.452)	(0.035)	(0.050)	(0.076)	(0.062)	(0.090)	
15M	0.001	1.212		-0.594	-0.685	**0.473**	**0.188**	0.001	0.054	0.055	0.58
	(0.132)	(0.911)		(0.330)	(0.428)	(0.034)	(0.048)	(0.070)	(0.060)	(0.085)	
18M	-0.004	1.291		-0.609	-0.739	**0.462**	**0.186**	-0.003	0.048	0.056	0.58
	(0.129)	(0.878)		(0.320)	(0.421)	(0.033)	(0.046)	(0.068)	(0.056)	(0.081)	
24M	0.001	1.149		-0.548	-0.673	**0.449**	**0.177**	-0.008	0.045	0.055	0.58
	(0.125)	(0.824)		(0.293)	(0.410)	(0.031)	(0.044)	(0.063)	(0.052)	(0.076)	

	Average Returns	Constant	Herd Measure (H_t^*)	Adverse Herding ($H_t^* I_t$)	Herding ($H_t^*(1-I_t)$)	EMR	SMB	HML	RAW	CMA	*Adj R2*
B. Value-Weighted Portfolio Returns (Five-factor model)											
3M	-0.021	**-0.539**				**0.431**	**0.217**	0.159	**0.277**	**0.326**	0.30
	(0.160)	(0.154)				(0.046)	(0.058)	(0.103)	(0.094)	(0.136)	
9M	0.000	**-0.505**				**0.394**	**0.245**	**0.205**	**0.288**	**0.269**	0.30
	(0.154)	(0.147)				(0.044)	(0.055)	(0.099)	(0.078)	(0.125)	
12M	-0.003	**-0.505**				**0.382**	**0.246**	**0.210**	**0.284**	**0.272**	0.30
	(0.151)	(0.144)				(0.043)	(0.054)	(0.093)	(0.076)	(0.119)	
15M	0.002	**-0.493**				**0.373**	**0.245**	**0.218**	**0.274**	**0.268**	0.30
	(0.149)	(0.141)				(0.043)	(0.053)	(0.089)	(0.074)	(0.116)	
18M	0.015	**-0.470**				**0.360**	**0.245**	**0.220**	**0.261**	**0.266**	0.29
	(0.147)	(0.138)				(0.042)	(0.052)	(0.087)	(0.073)	(0.114)	
24M	0.056	**-0.407**				**0.336**	**0.244**	**0.220**	**0.245**	**0.254**	0.29
	(0.142)	(0.133)				(0.041)	(0.050)	(0.086)	(0.069)	(0.113)	
3M	-0.021	-1.346	0.330			**0.430**	**0.217**	0.163	**0.280**	**0.330**	0.30
	(0.160)	(0.750)	(0.290)			(0.046)	(0.057)	(0.102)	(0.094)	(0.136)	
9M	0.000	-0.777	0.112			**0.394**	**0.246**	**0.204**	**0.289**	**0.271**	0.30
	(0.154)	(0.795)	(0.308)			(0.044)	(0.055)	(0.099)	(0.078)	(0.125)	
12M	-0.003	-0.534	0.012			**0.382**	**0.246**	**0.210**	**0.284**	**0.272**	0.30
	(0.151)	(0.779)	(0.303)			(0.043)	(0.054)	(0.093)	(0.076)	(0.120)	
15M	0.002	-0.096	-0.164			**0.373**	**0.245**	**0.219**	**0.274**	**0.262**	0.30
	(0.149)	(0.747)	(0.298)			(0.043)	(0.053)	(0.088)	(0.075)	(0.117)	
18M	0.015	-0.383	-0.036			**0.360**	**0.245**	**0.221**	**0.262**	**0.265**	0.29
	(0.147)	(0.734)	(0.294)			(0.042)	(0.053)	(0.087)	(0.073)	(0.115)	
24M	0.056	0.049	-0.190			**0.336**	**0.243**	**0.222**	**0.243**	**0.247**	0.29
	(0.142)	(0.667)	(0.270)			(0.041)	(0.050)	(0.086)	(0.070)	(0.113)	
30M	0.097	0.040	-0.159			**0.315**	**0.241**	**0.205**	**0.226**	**0.236**	0.28
	(0.136)	(0.617)	(0.253)			(0.040)	(0.047)	(0.084)	(0.065)	(0.112)	
36M	0.108	-0.437	0.058			**0.297**	**0.247**	**0.193**	**0.208**	**0.211**	0.28
	(0.130)	(0.549)	(0.224)			(0.040)	(0.044)	(0.079)	(0.061)	(0.108)	
3M	-0.021	-1.583		0.405	0.451	**0.431**	**0.217**	0.162	**0.281**	**0.331**	0.30
	(0.160)	(1.332)		(0.459)	(0.619)	(0.046)	(0.057)	(0.102)	(0.094)	(0.136)	
9M	0.000	0.369		-0.260	-0.482	**0.395**	**0.250**	**0.208**	**0.293**	**0.271**	0.30
	(0.154)	(1.371)		(0.481)	(0.640)	(0.044)	(0.055)	(0.099)	(0.078)	(0.125)	
12M	-0.003	0.775		-0.414	-0.668	**0.382**	**0.248**	**0.220**	**0.284**	**0.266**	0.30
	(0.151)	(1.324)		(0.470)	(0.620)	(0.043)	(0.054)	(0.093)	(0.075)	(0.120)	
15M	0.002	0.204		-0.262	-0.321	**0.372**	**0.246**	0.219	**0.276**	**0.262**	0.30
	(0.149)	(1.410)		(0.493)	(0.665)	(0.043)	(0.053)	(0.089)	(0.075)	(0.117)	
18M	0.015	-0.651		0.052	0.104	**0.360**	**0.245**	**0.220**	**0.261**	**0.264**	0.29
	(0.147)	(1.378)		(0.492)	(0.663)	(0.042)	(0.053)	(0.088)	(0.073)	(0.115)	
24M	0.056	0.216		-0.245	-0.278	**0.337**	**0.243**	**0.223**	**0.243**	**0.246**	0.29
	(0.142)	(1.314)		(0.461)	(0.637)	(0.041)	(0.050)	(0.086)	(0.070)	(0.113)	

Table 6 The effects of beta herding and sentiment on standardozed beta-sorted portfolios

For the sample period from January 1967 to December 2016, using past 60 monthly returns, every month we form quintile portfolios sorted on standardized-betas using non-penny stocks (>$1) and NYSE breakpoints. The equally weighted post-formation returns of the high-minus-low standardized-beta quintile portfolio is regressed on lagged beta herding in the presence of other control variables:

$$r^{\beta}_{High,t+f} - r^{\beta}_{Low,t+f} = \alpha + c_1 H^*_t + c_1 S^*_t + \sum_{k=2}^{K} c_k f_{k,t+f} + \varepsilon_{i,t+f},$$

where the forecasting horizon is set to f=3, 12, 15, 18, 24, 30, and 36, which are represented by 3M, 9M, … and 36M, respectively, and H^*_t and S^*_t represent our standardized-beta herd measure and Baker and Wurgler (2006) sentiment index, respectively. Overlapping portfolios are constructed to increase the power of the tests as in Jegadeesh and Titman (2001). The control variables include Fama-French five factors and ten factors we estimate using firm characteristics. The ten factors include the excess market return (EMR) and nine other factors which are accruals (Sloan, 1996); asset growth (Cooper, Gulen, and Schill, 2008); book-to-market ratio (Rosenberg, Reid, and Lanstein, 1985; Fama and French, 1992, 1993); gross profitability (Novy-Marx, 2010); size (Banz, 1980; Fama and French, 1992, 1993); momentum (Jegadeesh and Titman, 1993, 2001); net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004); net stocks issues (Fama and French, 2008); earnings surprises (Chan, Jegadeesh, and Lakonishok, 1996). These factors are return difference between the top and bottom decile portfolios. The coefficients on these nine factors are not reported. The numbers in the brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

	Average Returns	Constant	Lagged Herd Measure	Lagged Sentiment	EMR	SMB	HML	RAW	CMA	*Adj R^2*
A. Equally-Weighted Portfolio Returns (Five-factor model)										
3M	0.049	0.265	-0.231	**-0.288**	**0.528**	**0.171**	0.003	0.037	0.066	0.58
	(0.146)	(0.541)	(0.214)	(0.111)	(0.040)	(0.053)	(0.082)	(0.078)	(0.105)	
12M	0.013	0.682	**-0.416**	**-0.240**	**0.488**	**0.183**	-0.001	0.059	0.061	0.58
	(0.135)	(0.544)	(0.217)	(0.087)	(0.036)	(0.049)	(0.074)	(0.062)	(0.088)	
15M	0.001	0.932	**-0.523**	**-0.225**	**0.475**	**0.183**	-0.008	0.059	0.065	0.59
	(0.132)	(0.531)	(0.217)	(0.092)	(0.034)	(0.048)	(0.070)	(0.059)	(0.084)	
18M	-0.004	0.777	**-0.457**	**-0.176**	**0.463**	**0.181**	-0.010	0.050	0.063	0.58
	(0.129)	(0.487)	(0.201)	(0.084)	(0.032)	(0.046)	(0.067)	(0.055)	(0.081)	
24M	0.001	0.625	**-0.387**	-0.128	**0.450**	**0.172**	-0.014	0.044	0.062	0.58
	(0.125)	(0.427)	(0.179)	(0.090)	(0.031)	(0.045)	(0.065)	(0.051)	(0.077)	
30M	0.022	0.669	**-0.391**	-0.060	**0.436**	**0.165**	-0.022	0.033	0.056	0.59
	(0.122)	(0.422)	(0.177)	(0.079)	(0.030)	(0.044)	(0.062)	(0.048)	(0.073)	
36M	0.039	0.340	-0.242	-0.018	**0.423**	**0.168**	-0.032	0.025	0.055	0.59
	(0.119)	(0.406)	(0.171)	(0.071)	(0.030)	(0.044)	(0.061)	(0.046)	(0.072)	
B. Equally-Weighted Portfolio Returns (Ten-factor model)										
3M	0.299	0.395	-0.120	-0.191	**0.547**					0.66
	(0.156)	(0.422)	(0.120)	(0.108)	(0.037)					
12M	0.223	0.579	-0.211	**-0.207**	**0.511**					0.67
	(0.145)	(0.377)	(0.111)	(0.095)	(0.033)					
15M	0.220	0.644	**-0.238**	**-0.199**	**0.501**					0.67
	(0.142)	(0.361)	(0.107)	(0.092)	(0.031)					
18M	0.222	0.641	**-0.238**	**-0.176**	**0.493**	Nine Factors Controlled				0.67
	(0.139)	(0.350)	(0.106)	(0.087)	(0.030)					
24M	0.222	0.562	**-0.208**	**-0.180**	**0.478**					0.68
	(0.133)	(0.315)	(0.100)	(0.088)	(0.029)					
30M	0.230	**0.750**	**-0.283**	**-0.172**	**0.464**					0.68
	(0.128)	(0.297)	(0.096)	(0.081)	(0.027)					
36M	0.235	**0.640**	**-0.234**	**-0.158**	**0.452**					0.68
	(0.126)	(0.280)	(0.090)	(0.075)	(0.027)					

Table 7 Firm characteristics of portfolios formed on standardized-beta

For the sample period from 1967 to 2016, every month we form decile portfolios sorted on standardized-betas using non-financial and non-penny stocks (>$1) from the merged CRSP-Compustat database. NYSE breakpoints are used to form the decile portfolios. Following Fama and French (1992), all firm characteristics from July of year t through June of year t + 1 are calculated using accounting data for fiscal year-ends in calendar year t−1. For each decile portfolio, firm characteristics are calculated as follows. Market equity is calculated from the price times the shares outstanding from CRSP, Book-to-Market is shareholders equity plus balance sheet deferred taxes divided by ME, Sales Growth is the change in net sales divided by the prior-year net sales, External Finance is the change in the total assets minus the change in retained earnings divided by total assets, Asset Tangibility is property, plant and equipment divided by total assets, Dividend is dividends per share at the ex date times the shares outstanding divided by ME, and Profitability is the income before extraordinary items plus income statement deferred taxes minus preferred dividends divided by ME. Amihud illiquidity and idiosyncratic volatility are calculated as in Amihud (2002) and Ang et. al. (2006), respectively. For each decile portfolio, we calculate the median values except for standardized-beta and the beta where mean values are calculated. The right two columns show the average values and standard deviations of cross-sectional correlation coefficients between standardized-beta and firm characteristics.

	Decile Portfolios Formed on Standardized-Beta										Cross-sectional Regression of Standardized-beta on Firm Characteristics	
	Low	2	3	4	5	6	7	8	9	High	Average Coefficients on Firm Characteristics	Standard Error
Standardised Beta	-2.85	-1.51	-0.89	-0.43	-0.05	0.31	0.67	1.06	1.55	2.37		
Beta	-0.73	-0.56	-0.38	-0.19	-0.02	0.15	0.32	0.50	0.68	0.86	**0.981**	(0.000)
Market Equity	11.44	11.47	11.31	11.41	11.52	11.63	11.75	11.83	11.88	12.02	**0.681**	(0.017)
Book-to-Market	0.90	0.82	0.77	0.75	0.73	0.73	0.70	0.69	0.69	0.68	**-0.659**	(0.014)
Sales Growth (%)	7.75	8.38	8.95	9.50	9.71	9.54	9.89	10.09	9.74	9.82	**0.355**	(0.021)
External Finance (%)	4.47	4.35	4.39	4.61	4.70	4.63	4.93	5.09	4.86	4.90	**0.177**	(0.021)
Asset Tangibility (%)	28.08	23.30	22.47	22.42	22.07	22.23	22.93	22.75	22.51	21.58	**-0.122**	(0.029)
Dividend (%)	3.82	2.18	1.46	1.32	1.18	1.25	1.13	1.10	1.03	1.33	**-0.646**	(0.010)
Profitability (%)	10.12	10.11	9.85	9.84	9.72	9.71	9.78	9.94	10.07	10.23	**0.175**	(0.025)
Past 12 Month Returns (%)	1.06	1.29	1.32	1.37	1.44	1.50	1.47	1.49	1.41	1.33	**0.140**	(0.029)
Amihud iliquidity	0.21	0.23	0.21	0.22	0.19	0.16	0.15	0.13	0.11	0.07	**-0.665**	(0.012)
Idiosyncratic volatility	2.85	4.08	4.58	4.92	4.95	4.98	5.11	5.02	4.68	3.87	**0.417**	(0.015)

Table 8 The effects of beta herding on standardozed beta-sorted portfolios in other models

For the sample period from January 1967 to December 2016, every month we form quintile portfolios sorted on standardized-betas using non-penny stocks (>$1) and NYSE breakpoints. The post-formation returns of the high-minus-low standardized-beta quintile portfolio is regressed on lagged beta herding in the presence of other control variables:

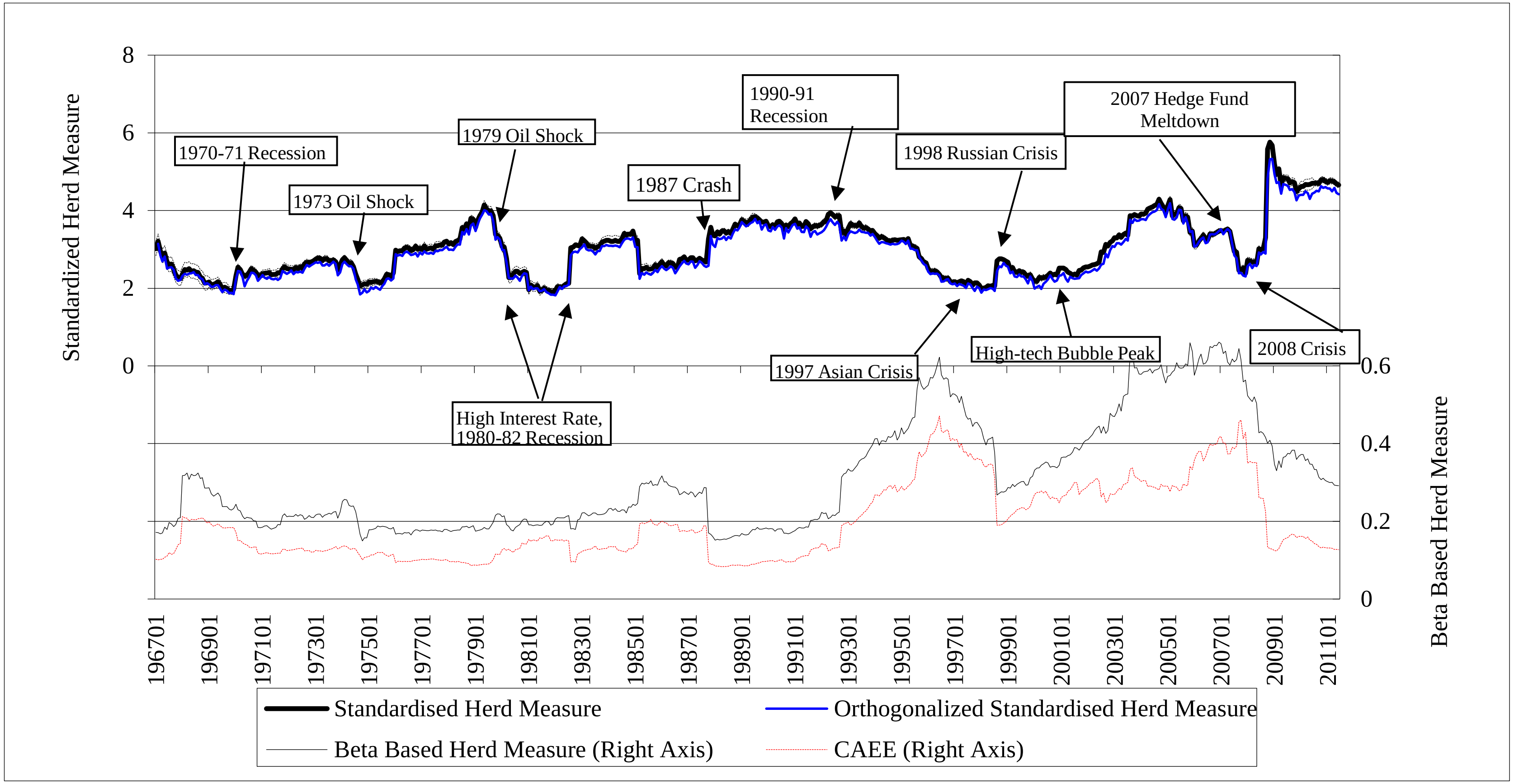
$$r^{\beta}_{High,t+f} - r^{\beta}_{Low,t+f} = \alpha + c_1 H^*_t + \sum_{k=2}^{K} c_k f_{k,t+f} + \varepsilon_{i,t+f},$$

$$r^{\beta}_{High,t+f} - r^{\beta}_{Low,t+f} = \alpha + c^+_t H^*_t I_t + c^-_t H^*_t (1 - I_t) + \sum_{k=2}^{K} c_k f_{k,t+f} + \varepsilon_{i,t+f},$$

where the forecasting horizon is set to f=3, 9, 12, 15, 18, and 24, which are represented by 3M, 9M, … and 24M, respectively, and $I_t = 1$ if $H^*_t > \frac{1}{T}\sum_{t=1}^{T} H^*_t$ and $I_t = 0$ otherwise. Overlapping portfolios are constructed to increase the power of the tests as in Jegadeesh and Titman (2001). The control variables include the excess market return (EMR) for the market model whereas they include nine other factors in the ten-factor model, which are accruals (Sloan, 1996); asset growth (Cooper, Gulen, and Schill, 2008); book-to-market ratio (Rosenberg, Reid, and Lanstein, 1985; Fama and French, 1992, 1993); gross profitability (Novy-Marx, 2010); size (Banz, 1980; Fama and French, 1992, 1993); momentum (Jegadeesh and Titman, 1993, 2001); net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004); net stocks issues (Fama and French, 2008); earnings surprises (Chan, Jegadeesh, and Lakonishok, 1996). These factors are return difference between the top and bottom decile portfolios. The coefficients on these nine factors are not reported. The numbers in the brackets represent Newey-West robust standard errors, and bold numbers show significance at the 5% level.

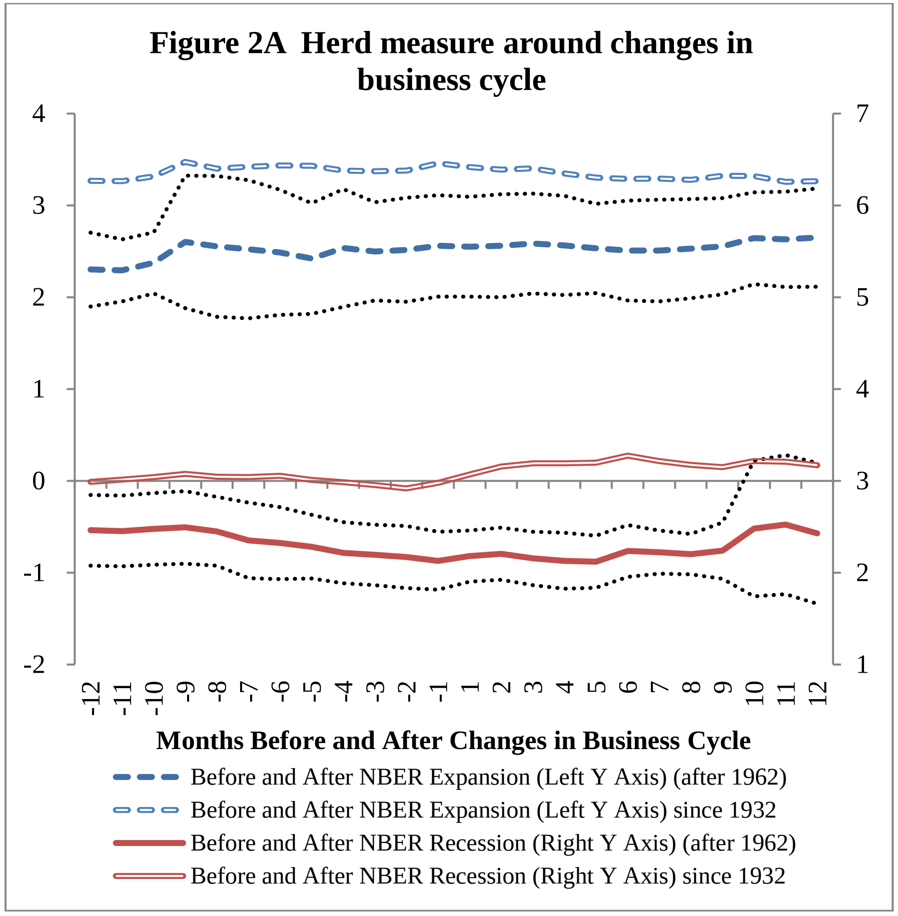
	Average Returns	Constant	Herd Measure (H^*_t)	Adverse Herding ($H^*_t I_t$)	Herding ($H^*_t(1-I_t)$)	EMR		*Adj R^2*
A. Equally-Weighted Portfolio Returns (Market model)								
3M	0.190	-0.048	-0.044			**0.844**		0.52
	(0.236)	(0.490)	(0.091)			(0.055)		
12M	0.161	0.352	-0.131			**0.812**		0.51
	(0.228)	(0.477)	(0.087)			(0.052)		
18M	0.154	0.338	-0.127			**0.786**		0.51
	(0.223)	(0.475)	(0.086)			(0.051)		
24M	0.165	0.175	-0.088			**0.768**		0.50
	(0.218)	(0.502)	(0.094)			(0.050)		
3M	0.190	-0.638		0.037	0.151	**0.844**		0.52
	(0.236)	(0.737)		(0.115)	(0.217)	(0.055)		
12M	0.161	0.071		-0.093	-0.038	**0.812**		0.51
	(0.228)	(0.708)		(0.109)	(0.202)	(0.052)		
18M	0.154	**1.592**		**-0.299**	**-0.543**	**0.792**		0.51
	(0.223)	(0.772)		(0.118)	(0.216)	(0.049)		
24M	0.165	**1.870**		**-0.319**	**-0.649**	**0.769**		0.51
	(0.218)	(0.813)		(0.127)	(0.216)	(0.049)		
B. Equally-Weighted Portfolio Returns (Ten-factor model)								
3M	0.299	0.365	-0.105			**0.548**		0.66
	(0.156)	(0.416)	(0.118)			(0.037)		
12M	0.223	0.562	-0.201			**0.511**		0.67
	(0.145)	(0.376)	(0.110)			(0.032)	Nine Factor	
18M	0.222	0.627	**-0.230**			**0.493**	Controlled	0.67
	(0.139)	(0.350)	(0.106)			(0.030)		
24M	0.222	0.543	**-0.198**			**0.476**		0.68
	(0.133)	(0.315)	(0.100)			(0.029)		
3M	0.299	0.645		-0.178	-0.259	**0.547**		0.66
	(0.156)	(0.688)		(0.178)	(0.302)	(0.037)		
12M	0.223	0.799		-0.263	-0.333	**0.511**		0.67
	(0.145)	(0.599)		(0.163)	(0.278)	(0.032)	Nine Factor	
18M	0.222	1.001		**-0.328**	-0.437	**0.492**	Controlled	0.67
	(0.139)	(0.544)		(0.153)	(0.258)	(0.030)		
24M	0.222	0.547		-0.199	-0.200	**0.476**		0.68
	(0.133)	(0.499)		(0.150)	(0.257)	(0.029)		

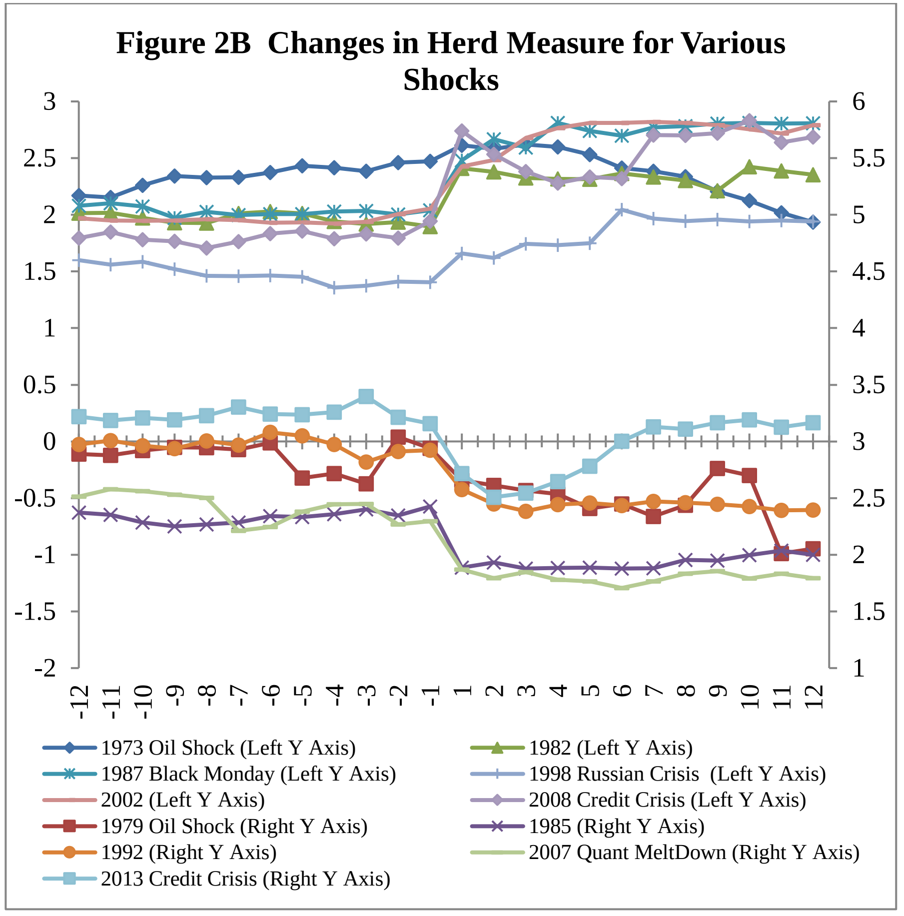
Figure 1 Beta herding in the US market



Past 60 past monthly returns in the merged CRSP-Compustat database are used to estimate betas in the Fama-French five-factor model. Empirical estimates of betas suffer various well-known problems. In particular, when prices do not reflect investors' expectations due to illiquidity, our measure may not fully reflect what it was designed to show, in particular, during market crises when liquidity dries up quickly. In order to avoid these unwanted effects and extreme returns associated with microstructure biases and thin trading, we omit non-penny stocks whose prices are less than $1 at the estimation month as well as stocks whose turnover (trading volume divided by shares outstanding) belongs to the bottom 1% or whose volatilities are excessively high or low (top and bottom 1%) during the past τ months. The top and bottom 1% of standardized-beta estimates (i.e., $(\hat{\beta}_i^b - \overline{\hat{\beta}^b})/\hat{\sigma}_{\hat{\beta}_i}$) are also omitted in our calculation of H_t^*. The beta-based herd measure is calculated with the cross-sectional variance of LS estimates of betas while the standardized herd measure is calculated with the cross-sectional variance of t-statistics of LS estimates of betas.

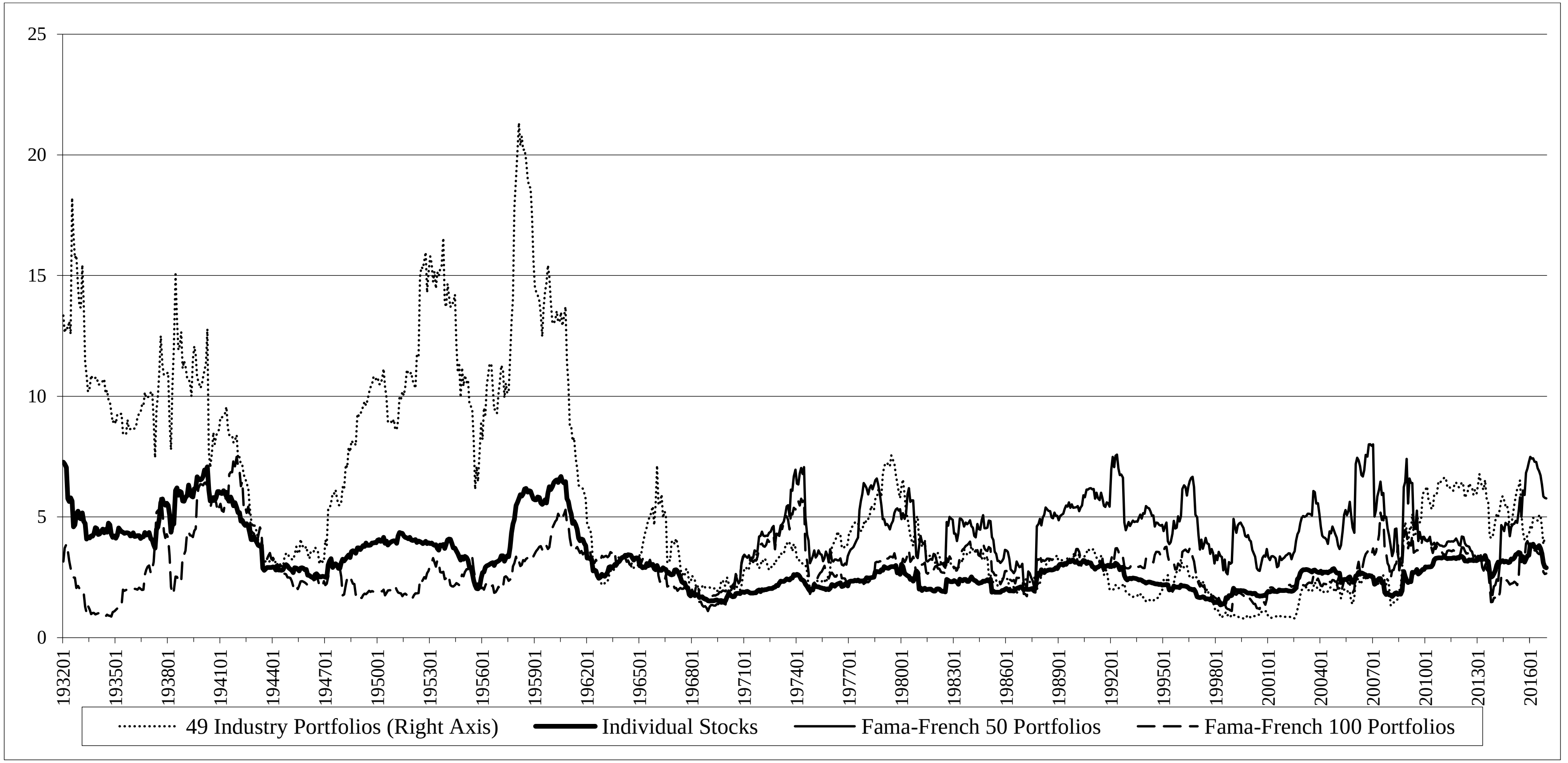
Figure 2 Herd measure and economic events





In Figure 2A the seven changes from recession to expansion (Before and After NBER Expansion) and from expansion to recession (Before and After NBER Recession) since 1962 are aligned at month 1. For each month, the average value of herd measure and its standard error are calculated. The dotted lines represent 95% confidence. For clear visual presentation, we plot the two cases to different vertical axes. In Figure 2B beta herd measure is plotted for eleven changes, all of which are aligned at month 1. The 95% confidence level is not plotted in Figure 2B, but the Mann-Whitney test results show that the changes before and after the shocks are all significant at the 5% level.

Figure 3 Standardized-beta herding calculated with various portfolios since 1932



We use the monthly data file from the Center for Research in Security Prices for stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. Every month we use 60 past monthly returns to estimate betas in the Fama-French five factor (the Fama-French three factor model with momentum before January 1967), which are obtained from Kenneth French's data library. The standardized herd measure is calculated with the cross-sectional variance of t statistics of betas, which are calculated with the Newey-West heteroskedastic adjusted standard errors. For herd measure with individual stocks, we omit stocks whose prices are higher than $1 (non-penny stocks) at the estimation point and whose past 60 monthly observations are available. We also do not use stocks whose turnovers belong to the bottom 1% or whose volatilities are excessively volatile or little volatility at all (top and bottom 1%) during the past 60 months. A statistical trimming process is used by omitting the top and bottom 1% of standardized-beta estimates in our calculation of the beta herd measure. Using 1,080 monthly observations from January 1927 to December 2016 and rolling windows of 60 months, we obtain 1,020 monthly herd measures from January 1932 to December 2016. For the herd measure for industry portfolios, we omit financial sectors and industries in which there are less than five firms at the time of estimation.